Adult Delta Smelt Entrainment Estimation and Monitoring Plan

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Introduction

To assist the USFWS with recommendations and decisions regarding water operations in the Bay Delta prior to and during the delta smelt (*Hypomesus transpacificus*) spawning period, in particular the months December through March, a procedure for estimating delta smelt entrainment (Delta Smelt Entrainment Estimation, DSEE) is proposed and described herein. In accordance with current conceptual models of delta smelt population redistribution and processes leading to elevated entrainment rates, the DSEE relies on data collected at higher frequencies than existing regular monthly surveys. Further, recent intensive sampling efforts deploying multiple tows in a single day at a single location [1] have shown that false absences are often recorded based on a single deployment of fishing gear. Hence, the conceptual and analytical framework of the DSEE relies on finer resolution and higher precision data about the spatial distribution and abundance of delta smelt than are currently collected by existing surveys. To provide these data, we recommend that a new monitoring program be established, referred to herein as the Delta Smelt Entrainment Monitoring (DSEM) program. Details on the survey design of the DSEM are also provided, in particular the number and spatial positioning of sample locations, the number of tows per sample location, and the frequency at which each location is sampled.

To provide a clear and structured statement of the problem, the model, and data, and how the data will be used, this proposal follows the proposed paper entitled "A Road Map for Planning a Biological Monitoring Program' by Knudson *et al.* [2], a ten step procedure for designing natural resource monitoring programs. This roadmap aims to (a) determine whether or not monitoring is necessary, and, if it is necessary, (b) ensure that resulting data will be meaningful and useful for guiding management decisions. The body of this report is structured according to these ten steps, while Appendix A is a concise summary of each of the steps. Detailed technical statistical and mathematical considerations are largely relegated to the appendices.

1 Problem

Delta smelt are an ESA and CESA listed species residing in the upper reaches of the San Francisco Estuary [3]. Water operations, particularly water exports by the State Water Project's Banks Pumping Plant (SWP), and the Central Valley Project's Tracy Pumping Plant (CVP), kill unknown numbers of sub-adult and adult delta smelt. Understanding how water operations translate into delta smelt entrainment towards the export facilities, and the concomitant mortality, is a complex endeavor not currently satisfactorily resolved despite some past efforts (see Appendix B), and has been identified by the Collaborative Adaptive Management Team (CAMT) as a priority topic area (topic 2). In particular, CAMT pointed to a ***current need to understand how Old and Middle River (OMR) flows can be used to manage adult delta smelt entrainment risk.***

Currently, decisions on water operations are made at relatively (to delta smelt life-stage durations) short time intervals. These include weekly meetings of the Smelt Working Group (SWG) and the Water Operations Management Team (WOMT), and even daily meetings by upper management staff across multiple agencies (USFWS, NMFS, etc.) at times with perceived movement of smelt towards export facilities. Recommendations and decisions on the amounts of water to be pumped are influenced by perceived entrainment risk, which is in turn imperfectly and loosely quantified in terms of numbers caught in fish salvage facilities, an index of delta smelt abundance for the period September-December based on the Fall Midwater Trawl (FMWT) survey, in-season measures of delta smelt abundance and spatial distribution throughout the Bay Delta using regular or special Spring Kodiak Trawl (SKT) surveys, and past and current storm events within a particular water year.

Water export related mortality is broadly identified with mortality resulting from physical entrainment that results in removal of fish from the estuary, termed *direct entrainment*. A second type of increased mortality from water operations is due to relocation to inhospitable locations of the Bay Delta (e.g. Clifton Court Forebay) that are associated with elevated risk due to predation in the South Delta, and are sometimes referred to as *indirect entrainment* effects. Throughout this proposal we will refer to both sources of mortality as simply *entrainment*. *Proportional entrainment*, the proportion of the population which experiences mortality due to entrainment in a given amount of time, measures the effects on the population abundance of entrainment related mortality, and the DSEE and DSEM are designed to evaluate proportional entrainment by which to conduct population viability analyses [4].

Previous efforts to understand adult delta smelt entrainment mortaility and proportional entrainment, and the current CAMT proposal on this topic [5], which outlines 4 new proposals to further improve understanding of processes leading to entrainment and its consequences at the population level, are summarized in Appendix B. These can be placed along a complexity spectrum, roughly characterized by the amount of temporal and spatial aggregation used when relating potential causal factors to estimates of entrainment. ***This proposal outlines the most temporally and spatially resolved approach for estimating adult delta smelt population distribution and survival, and proportional entrainment, proposed to date. This will enable a predictive framework to understand entrainment risk relevant on a management scale. Further, this framework will allow estimation of the effects of entrainment on the long-term population viability of delta smelt, providing a quantitative link between water management operations and the expected survival of delta smelt as a species.***

Glossary of key abbreviations and notations

CVP- Central Valley Project
$d_{t,\mathrm{HZ}}$- Number dying in the Entrainment Zone during time interval t
$d_{t,\mathrm{LZ}}$- Number dying in the Free Zone during time interval t
$d_{t,\mathrm{En}}$- Number entrained during time interval t
$\delta_{s,t}$- The density of delta smelt at location s over time interval t
DSEE- Delta smelt entrainment estimation
DSEM- Delta smelt entrainment monitoring
E_t- Entrainment related mortality, which is parameterized so that $E_t \geq 0$ with $E_t = 0$ corresponding to no entrainment related mortality
FMWT- Fall Midwater Trawl
HZ- High risk zone of entrainment, the region of delta smelt habitat where mortality rates include the direct and indirect effects of water exports at the CVP or SWP facilities
LZ- Low risk zone of entrainment, the region of delta smelt habitat where mortality is solely due to causes other than water exports at the CVP or SWP facilities
$m_{h,r,t}$- Number of stations in strata h of region r at time t
M_t- Natural mortality during time interval t, parameterized so that $M_t \geq 0$ with $M_t = 0$ corresonding to 100% survival
$n_{t,LZ}$- Total abundance during time interval t in the Free Zone
$n_{t,HZ}$- Total abundance during time interval t in the Entrainment Zone
$\tilde{n}_t$- Proportional entrainment during time interval t, equal to $d_{t,\mathrm{En}} / (n_{t,\mathrm{LZ}} + n_{t,\mathrm{HZ}})$
$p_{s,t}$- The probability of entrainment at location s and time t
ρ_t- A movement parameter accounting for the proportion of the population in the Free Zone moving staying within the Free Zone during time interval t
OMR- Old and Middle River, usually referring to flow in cfs
PSU- Primary sampling unit in multistage sampling. An approximately rectangular area of water with the longer sides oriented along the seaward flow of water, with length equal to 0.5km (the approximate distance covered in a 10 minute tow) and width ranging from 40m to 200m
$q_{i,h,r,t}$- The number of tows made at station i in strata h of region r at time t; $i = 1, ..., m_{h,r,t}$
t- Time index that represents an interval of time (e.g. $t = 1$ corresponds to the time interval December 1 to December 7)
SKT- Spring Kodiak Trawl
SSU- Secondary sampling unit in multistage sampling. The volume of water sampled by a single tow from the Kodiak trawl gear at a particular PSU. The number of SSUs per PSU depends on the size of SSU relative to the PSU.
SWG- Smelt Working Group
SWP- State Water Project, a water export facility
WOMT- Water Operations Management Team

2 Objectives

2a. Fundamental Objective: To protect and restore the delta smelt population.

2b. Means Objectives:

(i) To manage water operations to control adult delta smelt entrainment, to the degree possible, during December through March in a way consistent with protection and restoration of the population.

(ii) To estimate the abundance and spatial distribution of delta smelt to an acceptable degree of accuracy at time scales relevant to ecological and management processes, e.g. bi-weekly. Two distinct regions are identified within the delta smelt home range: (1) a high risk zone (HZ), in which delta smelt survival is concurrently affected by SWP and CVP water exports in addition to natural sources of mortality, and (2) a low risk zone (LZ) in which delta smelt survival is assumed to be unaffected by water diversions.

(iii) To establish a new monitoring program, the DSEM. Compared to the regular SKT survey, the DSEM survey will sample more frequently (e.g. bi-weekly), at fewer locations but with higher volumes sampled per location. Use the delta smelt catch and volume data from both surveys along with relevant environmental and hydrological variables to provide estimates of entrainment and proportional entrainment using the models of the DSEE. Models are fit which link management actions to changes in regional abundances and entrainment.

(iv) To use resulting fitted models and estimates of population level effects of entrainment to carry out Population Viability Analysis (PVA) to assess the long term effects of particular management operations under different population abundance and distribution scenarios. See Appendix E for further discussion.

3 Conceptual Model

We begin by defining entrainment in the context of adult delta smelt and water operations in the Delta as follows:

Definition 1 *Entrainment is the number of adult delta smelt that have died prior to reproducing because of water operations over and above the number that would have otherwise died prior to reproducing in the absence of water operations.*

There is a delicate point in this definition that is reflected in the term "over and above". Some fish which die due to water operations would have died from other causes (before reproducing) in the absence of water operations, and likewise, fish that would have died from water operations die from other causes. This is the phenomenon of competing risks [6]. This means that entrainment cannot simply be assessed by comparing the abundance decline from time t to $t+1$ in the presence of water operations with the abundance decline that would have been observed (over the same time period) in the absence of water operations. Such an estimate implies sequential rather than simultaneous mortality factors and the sequential estimate is an underestimate of entrainment.

In practice there is both a temporal and a spatial aspect to entrainment because the distribution of the population changes over time, and because changes in water operations and other hydrologic features affect the probability of entrainment. Figure 1 shows snap shots in time under several different hypothtical configurations of density distribution and entrainment risk. Intuitively, fish nearer the water pumping locations should have a higher probability of suffering mortality caused by water operations than fish further away for a given set of hydrologic conditions at time t, while changes in hydrologic conditions (e.g. export to outflow ratio) will change the probability of entrainment at a given location s. The larger the fraction of the population in the waters affected by pumping, the greater the magnitude of entrainment. These considerations lead to the following two notational definitions:

Notation 1 *$\delta_{s,t}$ is the density of delta smelt at location s and time t.*

Notation 2 *$p_{s,t}$ is the probability of entrainment at location s and time t.*

For simplicity the description of the spatial and temporal intervals over which these quantities are constant is deferred to Section 6. Estimating $\delta_{s,t}$ is achieved via the DSEM (see Section 7) and the quantitative description and model construction of $p_{s,t}$, along with the equations giving the total numbers entrained and the proportional entrainment, are described in detail in Section 6.

Remarks

- At any point in time there is a spatial region R where there is presumably no, or nearly no, entrainment related mortality, i.e. $p_{s,t} = 0$ for $s \in R$. We call this region the low risk zone (LZ), the boundaries of which may fluctuate through time.
- At any point in time there is a spatial region R where there is a relative high probability of entrainment, i.e. $p_{s,t} > 0$ for $s \in R$. We call this region the high risk zone (HZ), the boundaries of which may fluctuate through time.
- At any point in time there may exist spatial strata, e.g. LZ_{high} and LZ_{low}, within the LZ that contain relatively high densities and relatively low densities, i.e $\delta_{s,t} \gg \delta_{s',t}$ for $s \in \mathrm{LZ}_{high}$ and $s' \in \mathrm{LZ}_{low}$. Similarly for the HZ.
- An environmental variable which is currently used to manage perceived entrainment risk is the magnitude of Old and Middle River flows, a tidally averaged summary measure that reflects water exports and water inflows, among other things. OMR[1] is a covariate that affects $p_{s,t}$, where, at a given location s, as OMR becomes more negative (water is pulled upstream toward the pumps), $p_{s,t}$ increases and is higher for a location s_1 nearer the pumps than for a location s_2 further from the pumps, $p_{s_1,t} > p_{s_2,t}$ (compare the top two panels with the bottom panel in Fig. 1).

[1]The use of OMR as defined and used for management purposes has been questioned by Nancy Monsen in Appendix 2 of Anderson et al. 2014. In particular she notes “the export facility is located in the tidal zone of the south Delta and, [...] flows around those facilities cannot be simplified to daily, tidally-average velocities in this region. There is a flow towards the export facilities on every flood tide. As such, even when the OMR index reports a positive OMR flow, there are still two periods each 24-hour day during which tidal flood flow is towards the export facilities.”

- An environmental covariate thought to affect how $\delta_{s,t}$ changes in time is turbidity. It is hypothesized that delta smelt have a preference for more turbid waters [7]. Turbidity in the HZ is a factor considered in the week-to-week management of water operations. With all other factors fixed, and with OMR being negative valued, increases in turbidity might be associated with increases in entrainment risk because there is a higher probability that fish are in the HZ (compare the top two panels in Fig. 1).

- The major up estuary movement (i.e. changes in the $\delta_{s,t}$) resulting in a shift of the population from the Suisun Bay and Sacramento-San Joaquin rivers confluence areas to upstream locations thought to occur once rather than incrementally. Different models of movement (which covariates, or combinations of covariates) will be tested.

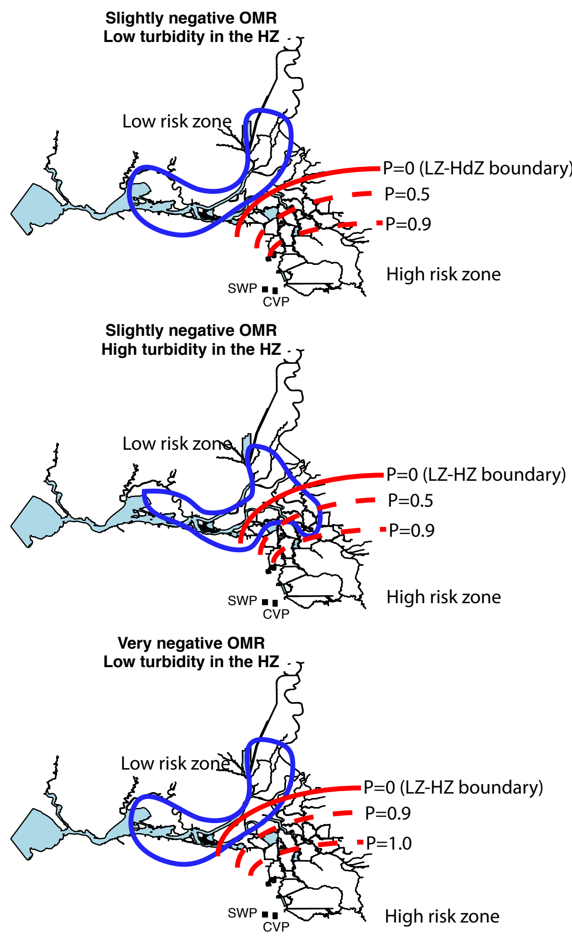

Figure 1: Hypothetical delta smelt peak abundance density distribution (outlined in blue), entrainment probability contours (shown as dashed red lines), and the low and high risk zone boundary (shown as a solid red line) for three different scenarios of Old and Middle River Flow and mean HZ turbidity. Conceptually, habitat conditions such as the distribution of turbid waters shape changes in the density distribution, while changes in water operations influence the entrainment probability field (note the change in the contour line values as well as their geographic shift in the bottom panel). The SWP's Harvey O. Banks Pumping Plant is located at the black square, and the CVP's C. W. "Bill" Jones Pumping Plant is located at the circle.

4 Actions

The primary management action taken regarding delta smelt entrainment is setting the timing and volume of water exports to achieve a specific OMR flow rate over a specific time interval, e.g. to manage OMR at -2000 cfs for three days in a row. The general thinking is to not have OMR be so negative that a "large" number of delta smelt are pulled toward the pumping facilities. Beginning in December and continuing through the month of March, weekly or more frequent (in February of 2015 it was daily during the period just after a storm) meetings are held by the Smelt Working Group (SWG) and the Water Operations Management Team (WOMT) to examine information about Delta Smelt catches in various fish monitoring programs (e.g. the Fall Midwater Trawl (FMWT) and the Spring Kodiak Trawl (SKT) surveys) and salvage from the pumping stations' fish facilities, and to make recommendations regarding water operations to the USFWS. Recommendations are partially guided by salvage take limits for delta smelt and perceptions of the adult delta smelt spatial distribution and abundance. Salvage take limits are calculated as the product of a constant (the "take multiplier") and the FMWT index. For example, the currently used take multiplier for 2015 is 21.81 and the FMWT index for 2014 is 9, resulting in a take limit of 21.81*9 = 196 (rounded).

The primary purpose of the new approach to assessing entrainment and the associated DSEM survey described herein is to provide more accurate information about spatial distribution and entrainment to SWG and WOMT to assist them in making their recommendations regarding water operations.

5 Approach Taken to Meet Objectives

The approach taken to meet the objectives involves a combination of data collection, data analysis, and reporting of the results of analyses to the SWG and WOMT on a regular basis throughout the period December through March. The steps in the process are as follows:

1. Coincident with the existing Fall Midwater Trawl and Spring Kodiak Trawl surveys, carry out a supplemental monitoring program, the Delta Smelt Entrainment Monitoring program (details provided in Section 7), to collect data on delta smelt densities throughout the Bay Delta. In contrast to the existing Spring Kodiak Trawl survey which samples about 40 locations on a monthly basis with a single tow per location, the DSEM will sample fewer locations while taking more tows per location more frequently, perhaps every two weeks[2].

2. On a periodic basis, e.g. bi-weekly, as new fish survey data and relevant environmental data (e.g, OMR and turbidity measures) become available, estimate the spatial distribution, abundance, and entrainment to date.

3. Provide these estimates of the current and past state of the system, along with standard errors, to the SWG and WOMT.

4. On an as directed basis, provide predictions (and prediction errors) of future entrainment under possible water operations plans under consideration by the SWG and WOMT. For

[2] Bi-weekly was thought the minimum effort required to estimate changes in distribution at a weekly time scale, the time scale for management decisions, and storm related density changes.

example, given the current state of the system (abundances in the LZ and HZ), predictions of entrainment are made for OMR levels of -2000 cfs, -3000 cfs, or -7000 cfs. Longer range predictions over the entire entrainment period, December through March, could be considered but would undoubtedly have large errors given the uncertainty in environmental variation in the delta (e.g. storm events), how $\delta_{s,t}$ will change through time, and actual export operations that effect $p_{s,t}$.

6 Quantitative Model of the System

This section formulates a mathematical description of the conceptual model described in Section 3. In contrast to the process model underpinning the draft Delta Smelt Life Cycle Model (DSLCM, [8]), the process model formulated here does not link cohorts, nor does it include reproduction. Instead, the dynamics of individual cohorts are modeled independently with a focus on adult survival and movement subprocesses.

For a given cohort, the "deterministic skeleton" [9] of the population dynamics is described by

$$\mathbf{n}_{t+1} = \mathcal{S}_t \mathcal{M}_t \mathbf{n}_t \tag{1}$$

where $\mathbf{n}_t$ is an $R \times 1$ vector of abundances in R different spatial regions at time t, and $\mathcal{M}_t$ and $\mathcal{S}_t$ are matrices whose elements describe the movement and survival in each region. Partitioning the delta smelt habitat into two regions, an LZ and HZ, and assuming movement only occurs from the LZ into the HZ, eq'n 1 becomes

$$\begin{bmatrix} n_{t+1,\mathrm{LZ}} \\ n_{t+1,\mathrm{HZ}} \end{bmatrix} = \begin{bmatrix} s_{t,\mathrm{LZ}} & 0 \\ 0 & s_{t,\mathrm{HZ}} \end{bmatrix} \begin{bmatrix} \rho_t & 0 \\ 1-\rho_t & 1 \end{bmatrix} \begin{bmatrix} n_{t,\mathrm{LZ}} \\ n_{t,\mathrm{HZ}} \end{bmatrix} \tag{2}$$

where ρ_t is the proportion of the subpopulation in the LZ staying in the LZ and can depend on covariates.

Survival in the LZ is determined by a single source of risk, $\exp(-M_t)$, where $M_t \geq 0$ is the "natural" mortality (as M_t gets larger, $\exp(-M_t)$ goes towards zero) and can potentially be modeled as a function of covariates. See remarks below. Assuming two simultaneous sources of mortality in the HZ, the natural one $\exp(-M_t)$ and an additional entrainment related source $\exp(-E_t)$, where $E_t \geq 0$ is a function of covariate(s) related to water operations (e.g. OMR), that operate simultaneously, ensures mortality risk in the HZ is at least as great as in the LZ. Assuming these models for movement and survival, the equations describing the population abundances through time become[3]

$$n_{t+1,\mathrm{LZ}} = \exp(-M_t)\rho_t n_{t,\mathrm{LZ}} \tag{3}$$

and

$$n_{t+1,\mathrm{HZ}} = \exp(-(M_t+E_t))\left((1-\rho_t)\, n_{t,\mathrm{LZ}} + n_{t,\mathrm{HZ}}\right). \tag{4}$$

Thus at time t the number lost to mortality in the LZ is

$$d_{t,\mathrm{LZ}} = (1-\exp(-M_t))\rho_t n_{t,\mathrm{LZ}} \tag{5}$$

[3]The formulation arises from the differential equation, $dn_t/dt = -(M+E)n_t$, which has the solution $n_t = n_{t-1}\exp(-(M+E))$. This solution holds when M and E are assumed constant over the time interval t to $t+1$.

and the number lost to mortality in the HZ at time t is

$$d_{t,\mathrm{HZ}} = (1-\exp(-(M_t+E_t)))\,((1-\rho_t)\,n_{t,\mathrm{LZ}}+n_{t,\mathrm{HZ}})\,. \tag{6}$$

The number $d_{t,\mathrm{En}}$ that die due to entrainment is

$$d_{t,\mathrm{En}} = \frac{E_t}{M_t+E_t}d_{t,\mathrm{HZ}} \tag{7}$$

and the proportion of the population that dies from entrainment $\tilde{n}_t$, i.e. proportional entrainment, is

$$\tilde{n}_t = \frac{d_{t,\mathrm{En}}}{n_{t,\mathrm{LZ}}+n_{t,\mathrm{HZ}}} \tag{8}$$

Remarks

- *Spatiotemporal resolution.* Movement and survival would be most accurately described as continuous processes in time and space where abundances and mortalities are obtained as integrals of continuous probability functions over space and time. We have attempted to formulate a conceptual and analytical model that might reasonably well approximate a dynamic process while recognizing the constraints inherent in field surveys. We have formulated a discrete time model because the data collected will likely be at weekly or bi-weekly intervals (see Section 7). Similarly, assuming only two distinct areas between which survival rates differ but which are constant within (over a particular time interval) is clearly inaccurate, but is needed because data will not be collected at very high spatial resolution. Having fewer spatial regions also reduces the minimum complexity of the movement model. We note that having a discrete model whose temporal resolution is not too fine somewhat ameliorates the inaccuracy of assuming constant entrainment related mortality across the entire HZ region.

- *Defining the LZ-HZ boundary.* The HZ will likely extend to approximately Prisoners Point or Jersey Point (see Fig. 1 and Section 7). It may be desirable to allow the boundary between the LZ and HZ to change in time. Exactly if and how this should be done (e.g. if it would change from year to year or week to week based on outflow levels) will be based on larger discussions with the scientific commuity.

- *Movement.* Movement ρ_t from the LZ into the HZ can be modeled as a function of covariates. As a simple example, if increases in flow out of the San Joaquin River near the confluence with the Sacramento River stimulate movement, then a model parameterizing the movement sub-process might be

$$\mathrm{logit}(\rho_t) = \beta_0+\beta_1 X_t \tag{9}$$

  where X_t is the QWEST (QWEST is the net flow of the lower San Joaquin River at Jersey Point) averaged over the time interval associated with time step t. More complicated models could involve turbidity in the lower San Joaquin, the role of Three Mile Sough, and relative outflow rates of the Sacramento and San Joaquin rivers. We also note that if movement is largely a one time event, then ρ_t will be one for most t. Formulating models for ρ_t will involve discussions with the larger scientific community, and collaborative interactions with findings from particle tracking models in the CAMT proposals may be beneficial. One option to adjudicate between competing hypotheses about movement is multimodel inference [10].

- *Survival.* As remarked above, survival is more accurately described as continuously changing in time and space. Although natural mortality, M_t, likely changes somewhat in time, initially it will be assumed M_t is constant in time as well as space. In the formulation given above, the proportion surviving in the LZ is $\exp(-M_t)$, so M_t must be positive and as the mortality increases $\exp(-M_t)$ should decrease. Parameterizing $M_t = \exp(\gamma_0)$ accomplishes this.

  Entrainment related mortality will be modeled as a function of covariate(s) that can be related to water management operations at the export facilities. For example, if entrainment mortality depends on Old and Middle River (OMR) flows, then

$$\ln(E_t) = \alpha_0 + \alpha_1 X_t \qquad (10)$$

  where X_t is the mean OMR flow over time interval t and we would expect α_1 to be greater than zero (i.e. as OMR becomes more negative and entrainment related mortality goes up, E_t must also increase). Different models of entrainment related mortality will be discussed with the larger scientific community.

  Note that entrainment related mortality E_t is simply quantifying mortality in addition to that experienced in the LZ. As such it is not necessarily entirely entrainment related mortality; survival in the HZ could simply be poorer (or better) in the absence of any entrainment. Arguing for cause and effect for any relationship between water operations and the parameter E_t needs to be done cautiously due to the necessarily observational nature of the data, i.e. a controlled experiment cannot be conducted. That said, a positive association between export levels and E_t, namely increases in exports translate into increases in the mortality rate parameter, would be consistent with a hypothesis that water operations are causing mortality over and above whatever baseline "natural" mortality occurs in the HZ[4].

7 Survey Design, Data Analysis, and Data Management

This section contains two subsections corresponding to the DSEM and DSEE, and a subsection on data management. The first provides details about the proposed sampling to be done by the DSEM program in order to obtain estimates of total population abundances. The second outlines how to use the information provided by the DSEM program to estimate the parameters of the model described in Section 6, and in particular how to estimate the different sources of mortality, the relationship of water exports to entrainment related mortality, and proportional entrainment.

[4]Observational studies have been used to argue for causation, e.g. smoking tobacco causes lung cancer. David Moore in his book *The Basic Practice of Statistics, Fourth Edition*, 2007 refers to five criteria identified by the US Surgeon General that can be used to make a case for causation without experimentation: (1) Strong Association, (2) Association consistent across studies, (3) Higher doses associated with stronger responses, (4) Alleged cause precedes the effect in time, (5) Alleged cause is plausible. The more criteria that are met, the stronger the case for causation. See also the 2014 Surgeon General's 978 page report "The Health Consequences of Smoking—50 Years of Progress: A Report of the Surgeon General, 2014" which is available online.

7.1 DSEM- Survey Design for Estimating Total Population Abundances

A brief summarization of the sample design is a temporally repeated stratified two stage (hierarchical) sample. The first sample will be taken at the beginning of December and will yield estimates of the abundances in each of the strata. The timing of subsequent samples could be regularly spaced, e.g. every two weeks, or could be somewhat aperiodic and triggered by changes in environmental conditions, e.g. a sizable precipitation event. For each point in time, a stage one sample is taken by selecting areas within each stratum. Stage two samples are multiple tows by a Kodiak trawl within each selected area. Details of the various aspects of the design for a given time point t follow but notation for time is omitted to reduce notation.

Stratification. Historical data suggests delta smelt are heterogeneously distributed across a range of spatial scales, showing high variability in catch per unit effort across tow locations separated by only 100's of meters (e.g. [1]) to 10's of kilometers (unpublished analyses of historic SKT survey data; also see [11] and [12]). At a single location, variability in catch between tows can also be substantial ([1], unpublished analyses of California Department of Fish and Wildlife side-by-side gear comparison special surveys data).

Acknowledging logistical constraints that preclude measuring fine scale variability across the entire delta smelt range, the approach taken here is to first spatially partition the habitat into two regions based on whether there is/is not a nontrivial chance of entrainment over the time interval of the model, what has been referred to previously as the Entrainment Zone and the Free Zone. Within each region, a further partitioning into strata is made, where the within stratum variation in delta smelt densities is presumably low relative to between strata variation in densities. In particular, two strata have been selected within each region, one designated "high density" and the other "low density". Figure 2 shows the two regions of the delta smelt habitat defined as the LZ and the HZ, and the two strata within each region.

Primary sample units and first stage sampling. Within each stratum in region r, a two stage sample is taken. Per stratum a sampling frame for the primary sampling units (PSUs) is constructed by subdividing the stratum into $\mathcal{M}_{h,r}$ (for stratum h in region r) exhaustive and mutually exclusive PSUs, e.g. polygons. The shapes of each PSU are roughly rectangular, and are more or less oriented such that the longer sides of the rectangles are roughly pointing upstream; see Figure 3 for an approximate example. The lengths of the PSUs, while not identical due to the irregular geometric shape of the strata, are approximately equal to the "distance" that could be covered by 10 minute straight line tows where the tow path intersects the latitude and longitude of the PSU center. The word distance is quoted because the distance traveled during a 10 minute tow can be highly variable depending upon the current. We are assuming an average PSU length of 0.5 km as an average (Lauren Damon, personal communication). The average width of a PSU is currently undetermined, but for the sake of discussion, and for some of the sample size analyses discussed later, we assume a width of 0.1 km. Details of the PSU sampling frames per stratum have not yet been worked out.

The first stage sampling within each stratum involves selecting the sample size, $m_{h,r}$, of PSUs from the total possible $\mathcal{M}_{h,r}$ PSUs in a given stratum. While there can be considerable fine scale variability in the density of fish, there is some degree of spatial correlation, i.e. spatially proximate regions of the Bay Delta are more likely to have similar densities than are spatially distant regions or PSUs. Given some level of spatial pattern, samples that more or less systematically cover a stratum, have “some degree of spatial regularity” [13], are preferable to simple random samples (see [14] for discussion of the merits of systematic sampling). There are various ways to select a spatially regular (systematic) sample over two dimensions and some ways are discussed in Appendix C.1, and one of these methods are recommended for actual data collection.

Secondary sampling units and second stage sampling. Within the i$^{\text{th}}$ selected PSU for sampling in stratum h of region r, $q_{i,h,r}$ tows are made along the longest axis of the PSU. Typically tows are made against the current, e.g. during an ebb tide, tows are made upstream. Implicitly, such a procedure implies that the tow paths are Secondary Sampling Units (SSUs). In a less dynamic setting, e.g. plots of land, the SSUs would be non-overlapping sub-plots which cover the PSU. However, having sampling crews locate non-overlapping SSUs in a body of water as well as keeping the sampling entirely within a chosen SSU is impractical. The fact that tides and outflows are continually moving water from what would be one SSU to another SSU within the time interval of sampling makes such a partitioning somewhat irrelevant. The main point is that exhaustively sampling a PSU is not feasible but multiple sub-samples are, and multiple tows will provide some measure of the within PSU variability in fish density. Details of the procedure for selecting tow paths within a PSU have not been worked out, but the general aim will be to get a representative sampling of the PSU. For example, given a rectangular PSU with a width of 125m and a Kodiak trawl width of 12.5m (Randy Baxter, personal communication), then the PSU can be divided into $Q = 10$ swaths of width 12.5m along the long arm of the rectangle (the SSUs). If $q_{i,h,r}$=5, then either the 1st or 2nd swath is randomly selected and every other swath is sampled. Again this is an idealization given the practical difficulties of exactly trawling such narrowly defined lanes but the general idea is to take a somewhat spatially regular sample.

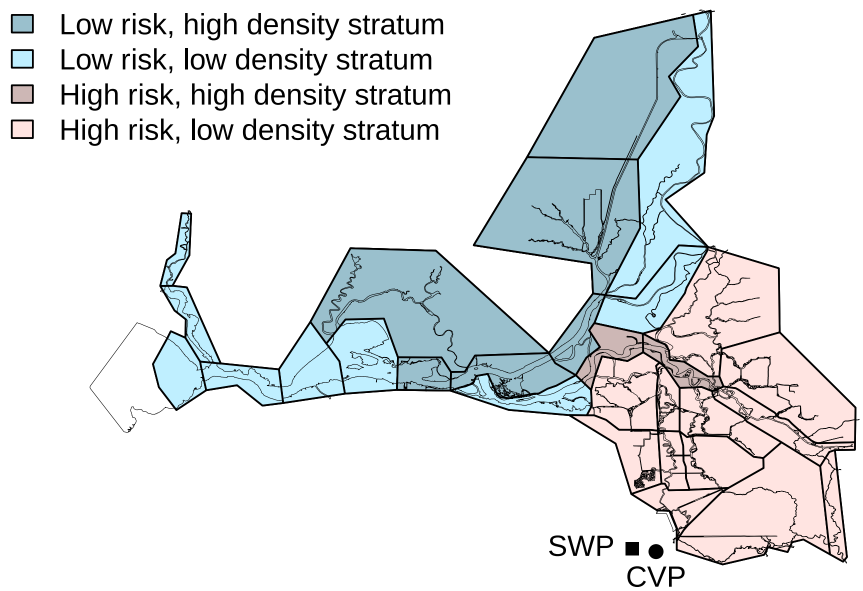

Figure 2: The proposed survey partitions the delta selt range into two regions, a LZ and a HZ, and within each region two strata deliniate subregions of high and low density. The SWP's Harvey O. Banks Pumping Plant is located at the black square, and the CVP's C. W. "Bill" Jones Pumping Plant is located at the circle.

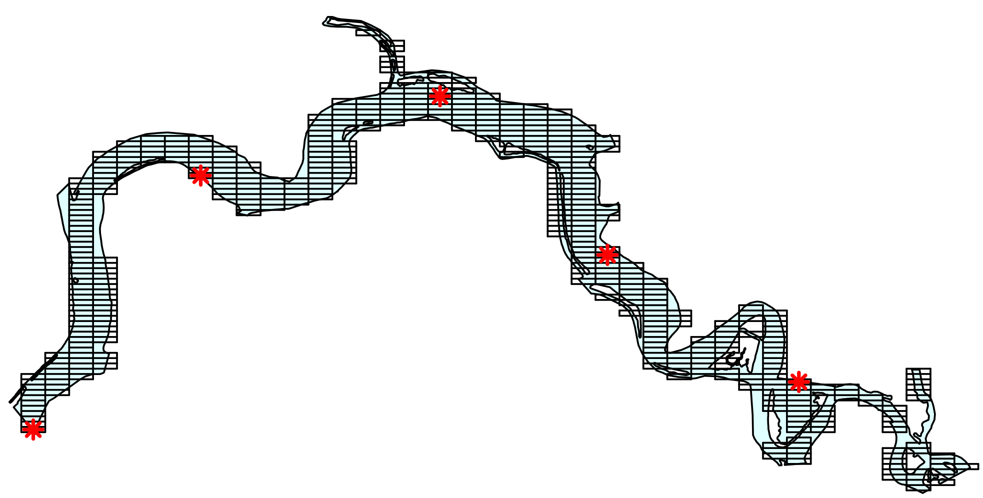

Figure 3: The high density HZ stratum overlain with potential sampling units shown as 0.1km by 0.5km rectangles. Potential primary sampling units (PSUs) are shown as rectangles, and subset of potentially chosen secondary sampling units (SSUs) are identified with red asterisks.

Sample size determination. Within each stratum there are two sample size problems to decide, the number of PSUs to sample ($m_{h,r}$) and the number of SSUs (number of tows, $q_{i,h,r}$) to sample within the i$^{\text{th}}$ selected PSU. There are various criteria for selecting sample sizes depending upon which parameters are of the most interest. Note that each particular PSU is allowed to have a different number of tows. Here we focus primarily on two parameters, the number of delta smelt entrained, $d_{t,\text{En}}$ (eq'n 7), and the proportion entrained, $\tilde{n}_t$ (eq'n 8). To get a rough idea of the effects of sample sizes on the quality of estimates of these parameters, a simulation study was carried out. The simulation procedure was as follows:

1. The Bay Delta region was divided into the four strata described previously.
2. PSU volumes were assumed constant and the same for all strata, 1 km length by 0.1 km width and 4m depth.
3. Initial average delta smelt densities (at time t_0) for the high and low density strata of the Free Zone and the Entrainment Zone were calculated using catches from routine SKT sampling in February 2015. See Appendix C.1 for details on the density estimation procedure.
4. Average densities in the LZ after mortality occurred (at time t_1) were fixed deterministically at 0.92 of the initial density ($\exp(-M) = 0.92$), while average densities in the HZ were fixed at $0.92 \times \exp(-E)$, where different values of E were examined, e.g. $\exp(-E) = 0.9$ or 0.5. In this section we present results based upon $exp(-E) = 0.5$. See Section C.1 for results using $exp(-E) = 0.9$.
5. Abundances in each PSU for each time period were generated according to a Poisson distribution with mean parameter the product of the stratum- and time-specific densities and PSU volume.
6. Tows of constant volume, 5000m^3, were assumed and abundances within each tow were generated according to a Poisson distribution using an appropriately scaled mean parameter (based on the stratum-specific density).
7. Sample sizes m and q were identical for all four strata and simple random samples of PSUs and SSUs were selected.
8. Method of moments estimates of $d_{t,\text{En}}$ (see eq'n 19 in Appendix C.2.2) were calculated using strata estimates of abundance, $n_{t_0,\text{LZ}}$, $n_{t_1,\text{LZ}}$, $n_{t_0,\text{HZ}}$, and $n_{t_1,\text{HZ}}$. The abundance estimates were volume-weighted expansions of the estimated average sample densities within each stratum.

The results of the simulation are summarized in Figure 4, which shows the estimated mean and 95% confidence interval for each parameter. With only two locations per stratum and two tows per location, there is considerable variability in the estimates for all eight parameters. Precision can be improved by increasing the number of locations, increasing the number of tows, or both. The largest gains in precision occur when going from two to four locations per stratum, and from two to four tows per location. For example, the coefficient of variation for $d_{t,\text{En}}$ decreases about 30% when going from two to four locations per stratum, and decreases by a similar amount when going from two to four tows. The percentage of times that the method of moments estimate was negative is shown in Table 1.

Table 1: Percentage of times $d_{t,\mathrm{En}}$ was negative.

Locations per Stratum	Tows per Location: **2**	**4**	**6**	**8**
2	23.1%	14.6%	9.9%	6.8%
4	15.0%	7.0%	3.2%	2.3%
6	10.0%	3.9%	1.5%	0.4%

The CV for proportional entrainment, show in Table 2, is relatively large for the location and tow values considered here, indicating poor estimability. If a CV less than 50% was acceptable, then combinations of (m, q) of (4,6) and (6,4) would work. To get some idea of what might be an acceptable CV, consider a crude 95% confidence interval based upon $\pm$ 2 standard errors, where standard error = $\tilde{n}_{t_0} CV$. Depending on $\tilde{n}_{t_0}$ and the CV, unrealistic confidence intervals outside (0,1) could result. Note that confidence intervals will not be constructed in such a simplistic way, however.

Table 2: Mean CV for proportional entrainment, $\tilde{n}_{t_0}$.

Locations per Stratum	Tows per Location: **2**	**4**	**6**	**8**
2	155.7%	99.1%	79.5%	68.3%
4	99.3%	69.5%	56.1%	49.8%
6	79.5%	57.6%	46.1%	39.9%

Table 3 shows the total number of tows per sampling period as prescribed by each of the twelve location-tow combinations represented in Figure 4. Under a bi-weekly sampling schedule, this would be the total number of tows carried out every two weeks. Suppose one chose a target CV for $\tilde{n}_{t_0}$ of 50%, say, the number of tows required is over twice the total monthly samples taken by the current SKT survey (with about 40 tows).

Table 3: Total number of tows per sampling period assuming a total of four strata.

Locations per Stratum	Tows per Location: **2**	**4**	**6**	**8**
2	16	32	48	64
4	32	64	96	128
6	48	96	144	192

The results from this sample size analysis are tentative in that assessment of the quality was based on simulation procedures which do not necessarily reflect the likely nature of the real data. Hopefully, the simulation results are unduly pessimistic in contrast to what might happen in reality. Specific simplifications of the simulation compared to reality include (1) spatial heterogeneity (i.e. no spatial patterns) between PSUs and SSUs), (2) simple random sampling (as opposed to spatially regular or systematic samples), (3) simple volume expansions of stratum abundances (as opposed to estimates based on a spatially regular design, say), and (4) method of moments estimates of $d_{t,\mathrm{En}}$ (in contrast to least squares estimates, for example). The simplification likely most critical was spatial heterogeneity. If a spatial pattern to the densities had been generated, then a systematic sample could have yielded more precise estimates of stratum- and time-specific estimates of abundance. In addition to some evidence for spatial patterns, empirical evidence from the SKT surveys suggest between location variation that is greater than Poisson variation, in particular zero inflation is a possibility. The effect of taking simple random samples rather than systematic samples is unimportant without a spatial pattern, as both are statistically equivalent in the case of spatial heterogeneity. Method of moments can lead to physically unrealistic estimates such as negative entrainment and survival probability greater than one. Constrained estimation methods can be used as an alternative (see Appendices C.2 and D for examples of avoiding impossible values. However, method of moments estimators, while likely less statistically efficient than other procedures like least squares, appeared unbiased in this case. Appendix C.1 includes more discussion of the simulation procedure and alternative approaches. Additional research is underway to explore more realistic density processes with spatial patterns along with spatially regular sampling schemes.

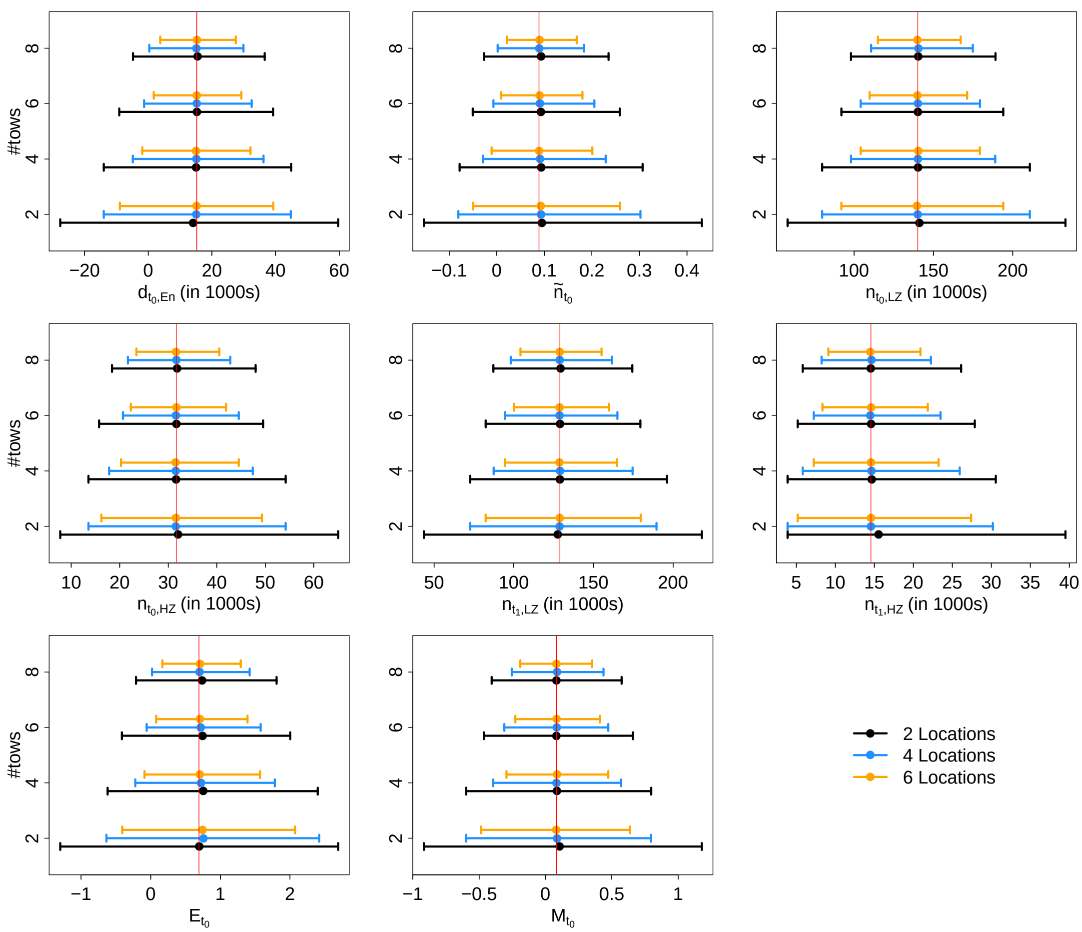

Figure 4: Empirical means and 95% confidence intervals for eight parameters (defined below) based on simulations from a two-stage sampling design with varying numbers of sampling locations per stratum and tows per location. Each mean and corresponding confidence interval is based on 5000 simulations. Vertical red lines indicate "true" values used to generate the data. Parameters shown are: $d_{t_0,En}$ (number entrained between t_0 and t_1), $\tilde{n}_{t_0}$ (proportional entrainment between t_0 and t_1), $n_{t_0,\mathrm{LZ}}$ (LZ abundance at t_0), $n_{t_0,\mathrm{HZ}}$ (HZ abundance at t_0), $n_{t_1,\mathrm{LZ}}$ (LZ abundance at t_1), $n_{t_1,\mathrm{HZ}}$ (HZ abundance at t_1), E_{t_0} (entrainment related mortality between t_0 and t_1), and M_{t_0} (natural mortality between t_0 and t_1).

7.2 DSEE- Applying the Data to Estimate Entrainment

Data analysis needs to accomplish the following estimates for each time step t:

1. *Estimation of Region Abundances*- Total abundance in each of the regions (i.e. the LZ and HZ) will be estimated by calculating mean densites per strata, expanding these strata level density estimates by strata water volumes to obtain strata level abundances, and then summing these strata abundances within each region to obtain estimates of absolute abundance. See eq'ns 12 and 13 in subsection C.2 in Appendix C.

2. *Estimation of movement and survival*- The movement and survival subprocesses given by eq's 1 in Section 6, which produce expected population abundances in each region, will be estimated using the regional abundance estimates calculated in step 1. This will initially be accomplished by fitting a process noise only time series model with expected values described by the deterministic predictions from eq'n 1, which include equations describing the subprocesses of movement and survival, e.g. eq'ns 9 and 10 (also see subsection C.2.2 in Appendix C).

   This step will also provide estimates of parameters in models describing relationships between manageable water conditions, e.g. OMR, and entrainment mortality (e.g. the α's in eq'n 10). We note that, while not necessary in the model formulation of Section 6, the use of concurrently collected salvage data may be leveraged to facilitate model fitting if a good model relating observed salvage to numbers entrained can be constructed. See Appendix D for an example and further elaboration.

3. *Estimation of numbers entrained*- Use the fitted model parameters and abundance estimates in the HZ along with eq'n 6 and 7 to estimate the total number entrained $d_{t,\mathrm{En}}$.

4. *Estimation of proportional entrainment*- Use the fitted model and estimates of the total abundances and the numbers entrained to estimate proportional entrainment $\tilde{n}_t$ using eq'n 8. Over time (possibly multiple years, see remarks below), these estimates can be used to estimate how water exports influence the population level growth rate and analysis of population viability under different future export scenarios.

Remarks

- Abundance estimation uncertainty, model misspecification, and model complexity all will contribute to challenges in immediate use of the DSEM and DSEE to give precise quantitative support for management decisions.

- Reliably disentangling the different sources of mortality and parameterizing relationships between water exports and the population growth rate may take several field seasons of data. Fitting population dynamics models and obtaining precise estimates with limited data can benefit from observations spanning a range of population densities [15]. The utility of the model to provide guidance across a range of environmental conditions (e.g. inflow and turbidity), export rates, and densities, will depend on past combinations of these variables used to fit the model.

7.3 Data Management

Tow specific catch and environment data will be collected according to the SKT protocol. Data will be input to USFWS computer storage facilities and cleaned datasets subject to quality analysis and quality control will be made available for the public and analysts. Cleaned datasets will be produced within one week of collection in the field to facilitate real time adaptive management decision making.

8 Data Collection

The existing monthly CDFW SKT surveys would presumably continue, as would sampling at the SWP and CVP fish facilities for salvage. The new sampling plan described in the previous step (the DSEM) would likely be carried out on a relatively frequent basis, either regularly, say bi-weekly, or aperiodically as triggered by changes in environmental conditions deemed significant. Relevant environmental and hydrological covariate data, OMR flows, turbidity, export volumes, and measures of outflow would presumably be available from agencies currently collecting such data, e.g. USGS monitoring stations for turbidity.

For the DSEM program, Kodiak trawl gear would be used for catching delta smelt. Analysis of the data provided by side-by-side gear evaluation studies conducted during 2012-2014 have indicated that at least for the sub-adult and later life stages, surface trawling with Kodiak gear catches significantly more delta smelt than other gear types currently used by CDFW and USFWS to sample fish species in the Bay Delta.

We note that the study by [16] on using underwater video technology to survey for delta smelt using the so called “SmeltCam” offers an intriguing alternative to traditional methods that haul fish onboard a survey vessel. SmeltCam technology might provide an understanding of the vertical and lateral distribution of delta smelt as it is the simplest means of identifying exactly where in the water column and where relative to the shoreline a fish is positioned. If there are local spatial gradients to smelt densities, e.g. the maximum density is 2m below the surface and decreases to zero by 10m below and decreases to zero at the surface, then understanding of the nature of the spatial gradient could be brought to bear in the analysis of the gear efficiency studies, which in turn would affect estimates of gear-specific capture probabilities. Further, SmeltCam is a non-destructive, or at least less destructive, sampling protocol than traditional surveying. As SmeltCam technology becomes more available, it may replace Kodiak Trawling as the primary survey tool. Running Kodiak Trawl and surface towed SmeltCam side by side may be needed for gear comparison and calibration purposes.

9 Data Analysis and Reporting

9.1 DSEM Data Analysis

To provide information in a timely manner to the SWG and the WOMT, analysis of data collected by the DSEM could be a full time job for one or more individuals during the months of December through March. Depending on the temporal sampling frequency, updated estimates of abundances by region and estimates of entrainment to-date should be produced as new sampling data becomes available.

9.2 Historical Spring Kodiak Trawl Data Analysis

In addition to the proposed data collection and analysis objectives oulined here, existing data from the SKT now spans over a decade (2002-2015). Analysis of these monthly collected data in conjunction with monthly statistics (e.g. averages or extremes) of hydrological data such as OMR, QWEST, or exports, may provide insight into relationships between spatially resolved adult abundances and hydrological data at the monthly or annual time scales. This information is part of the aim of the DSLCM [8], so such analyses could possibly support DSLCM work or be informed by it. Exploratory data analysis of the relationships between measaures of population abundance and changes in abundance using SKT data, along with relatively simple models that e.g. describe abundance in the South Delta as a function of OMR, can be done relatively easily.

9.3 Management Specific Advice

The ideal approach to inform management actions would be to have a quantitative understanding of the relationship between water management operations (i.e. weekly) exports from the CVP and SWP and the long-term population viability, given system wide biological and environmental metrics such as current total abundance, inflow, outflow, turbidity, predators, and food. Such a metric will not be available until after enough data are available to fit models such as those described in Section 6, and the applicability of the estimated relationships will depend on the range of conditions observed that provide the data used for mode fitting. These considerations suggest both short- and long-term uses of the data:

- *Short-term.* The proportion of the population in the HZ, and hence vulnerable to entrainment, can be calculated in a straightforward manner. Because the DSEM is proposed to operate at a weekly or bi-weekly time scale, this proportion will be immediately available to managers for “real time” estimates of population level risk. Note that it would not be possible to relate the value of proportional entrainment to a change in population level growth rate with only this information.

- *Long-term.* In the long-term, perhaps after several years of data collection, relationships between system state variables, the proportion of the population entrained, and the contribution to the decline in the population level growth rate due to entrainment will be availabe. These estimates can be used to calculate PVA type analyses (see Appendix E). When estimated relationships will be available, their unbiasedness and precision, and their applicability, will depend on the range of observed conditions going forward and correct model specification. In a simple dichotomy of exports, environmental conditions, and initial adult densities, it would be necessary to observe each of the 8 total combinations of factors describing high vs. low inflow, high vs. low exports, and high vs. low adult abundance to ensure a foundation for making predictions of managment actions to population level growth rates in emerging “real time” situations.

10 Model Updating and Post-Hoc Assessment of Data Collection and Analysis Procedures

At the end of each entrainment season, all the data gathered for the year would be appended to previous data set, models are re-fit using the extended data set, yielding updated parameter estimates, including estimates of entrainment. Estimates of the year-on-year population growth rate, e.g. the ratio of the estimated total abundance of cohort in February of the current year to the estimated total abundance of February in the preceding year, could then be related to water operations, inflow, and past abundances. Parameter estimates for sub-models relating environmental covariates to movement and water operations to entrainment would be updated by refitting models using the newly expanded historical data set.

11 Future Analyses and Refinements

- Sample size determination could be improved by including spatially structured density gradients into predictions of abundance, as well the use of spatial sampling procedures, e.g., regular grid sampling.

- An eventual product is a management tool which explicitly links water operation management actions (throughout the entire entrainment period) to the expected entrainment, in both absolute numbers as well as a proportion of the population. Such a tool would aim to answer questions like the following. Given an initial population size at the beginning of December of 200,000 delta smelt where 10,000 are in the HZ and 190,000 are in the LZ, assuming a movement of 10% from the LZ to the HZ during the middle of January, what would be the population-level effect of holding OMR flow to -2000 cfs throughout the four month period (December-March)? Table 4 shows a hypothetical example of how proportional entrainment is influenced by OMR and CCFB turbidity for given total abundances in the LZ and HZ.

Table 4: Hypothetical proportional entrainment $\tilde{n}_t$ as a function of mean OMR (cf^3/sec) over the sampling period and CCFB turbidity (NTU).

	CCFB Turbidity			
OMR	5	10	15	20
-1000	0.10	0.20	0.30	0.35
-2000	0.12	0.22	0.32	0.37
⋮	⋮	⋮	⋮	⋮
-10000	0.20	0.30	0.40	0.45

- Beyond increasing rates of adult mortality, entrainment also impacts larval and sub-adult life stages. To assess the effects of entrainment mortality on all life stages requires the complete Delta Smelt Life Cycle Model (DSLCM) [8] and the proposed DSEE analysis is an interim product leading to the DSLCM.

- Assessment of longterm effects of various management actions can be done in the context of population viability analysis (VPA). Such a VPA would include the effects of entrainment on all life stages while controlling for other sources of mortality such as food limitation and contaminants (see [17] for evidence of food limitation and contamination stress) as well as predation.

- Dynamic, real-time selection of PSUs (sampling locations) might be implemented in a statistically efficient way. As new information about the fish density field is gained, sample selection probabilities might be modified to improve sampling efficiency. E.g. if VPS is used, the inclusion probabilities that were proportional to perceived densities would be modified.

- Dynamic determination of the number of SSUs (number of tows) to be selected at a given site might be advisable for lessening "take" numbers, particularly in regions of relatively high density. Just what the "stopping rules" should be is a topic of additional research.

- Theoretical determination of stage 1 and stage 2 sample sizes, $m_{h,r}$ and $q_{i,h,r}$, respectively, is an alternative to the simulation-based approach presented here. If a closed form solution for the variance of a parameter estimate is available, then one can calculate suitable combinations of $m_{h,r}$ and $q_{i,h,r}$ for a specified coefficient of variation.

Acknowledgements

We thank Lauren Damon and Randy Baxter from the CA Department of Fish and Wildlife for helpful discussion on Kodiak Trawl sampling. Melinda Knutson provided clarification on specification of objectives classification in the context of the Monitoring Road Map.

APPENDICES

A A Ten Step Road Map for Designing a Biological Monitoring Program

The ten steps in the proposed paper "A Road Map for Planning a Biological Monitoring Program" by Knudson *et al.* [2] are as follows, with italicized comments added.

1. Define the problem. *This is a statement describing the stimulus for considering establishing a monitoring program.*

2. State objectives. *This answers the question "Why do this?" with a statement as to what the Fundamental Objective(s) is, and provides general answers to the question "How to do this?", where the answers are known as Means Objective(s).*

3. Sketch a conceptual model of the system. *This includes descriptions of the system components including subprocesses, primary input variables, covariates, response variables, and relationships between components.*

4. Specify action(s) or confirm none planned. *For this monitoring program actions are indeed planned, namely actions to manage entrainment losses in order to protect and rebuild the delta smelt population.*

5. Decide on an approach. *For some problems, a one time sampling, an inventory, suffices, and for other problems, focused relatively short-term research will provide the desired information. In these cases, the Road Map ends with this step. In other cases, sampling repeatedly over time, i.e. monitoring, is determined necessary.*

6. Translate model into quantitative form. *This includes translating the conceptual model from Step 3 into numerical equations which typically include unknown parameters which will be estimated from monitoring data. This is sometimes called a process model.*

7. Design the survey, the analytic approach, and the data management system. *This can include the details of the sample design, sample sizes, data collection procedures (protocols), specification of quantitative models linking the collected data to the underlying system components (observation model), and how the data will be used to fit the quantitative model in Step 6.*

8. Collect data. *Note that the step of actually gathering data is just one of ten steps.*

9. Analyze data and report. *This ensures that the data are actually used and the results are made available.*

10. Update model(s), assess, or plan and implement action(s), when relevant. *This step includes reconsideration of previous understanding of the system (particularly Steps 3 and 6), evaluates the effects of actions if they occurred, and examines the data collection procedures. After completing this step, the road map cycles back to Step 8.*

B This Proposal in the Context of Other Past and Current Entrainment Analyses

Previous estimates of how entrainment affects the smelt population have focused on trying to measure proportional entrainment, although no analysis has explored in a quantitative way the consequences of various levels of proportional entrainment. These estimates have been made using relatively broad summary statistics by making volumetric expansions of density estimates within and outside the Entrainment Zone (e.g. [18, 19]), as well as by building more complex models that include covariate dependence (typically OMR) on the numbers appearing in salvage (e.g. [20, 7, 21]). Critiques on such past efforts (and also the current CAMT proposal, see below) span a range of issues, from data shortcomings to conceptual assumptions to a lack of a quantitative measure on the impacts of entrainment on delta smelt population viability. These shortcomings are discussed next.

Data limitations of current existing monitoring programs are perhaps the least controversial. A common data shortcoming variously recognized in these analyses is reliance on monthly catch data to accurately estimate entrained and unentrained abundances because these data are relatively coarsely sampled in time and space. Although Miller [18] assumed 100% gear efficiency by the Kodiak Trawl, increasingly it is recognized (see for instance [1]) that even Kodiak Trawl gear can require significantly more than the single tow normally carried out during regular surveys to detect delta smelt when their densities are low. The covariate analyses have been done using either annual indexes of abundance [7, 21] or expanding surveys of one to several days to represent density for an entire month [20], both too coarse for the time scales at which spawning movement and entrainment events are believed to occur. In addition to spatio-temporal density estimation issues related to data sampling frequency, salvage data is recognized to be a potentially very poor proxy for entrainment [22].

Beyond data adequacy issues, perhaps the most striking difference between the proposal described here and past work is that no approach to date has simultaneously attempted to model movement and survival, the two most salient sub-processes determining population dynamics of spawning delta smelt (see Appendix D for a feasibility study). The current CAMT proposal [5] in its entirety does consider both movement (Proposal II) and survival (Proposal III) separately with the aim to integrate findings of movement into revised estimates of proportional entrainment (the differences between the CAMT projects and our proposal is discussed next). A potentially important shortcoming in all past and current entrainment analyses is that disentangling natural from entrainment mortality has not be attempted. It is our opinion that an essential consideration when estimating the effects of entrainment on delta smelt population viability is that not all delta smelt entrained would have otherwise survived to reproduce (see Section 3). Ignoring this consideration potentially biases upwards the estimate (and importance) of propotional entrainment.

Efforts to address some of these shortcomings, and in particular the use of salvage data, movement, survival, and population level effects of entrainment, have been proposed (and funded) with the current CAMT proposal titled "Understanding Population Effects and Factors that Affect Entrainment of delta smelt at State Water Project and Central Valley Project" [5]. The review of this proposal, available at `http://deltacouncil.ca.gov/event-detail/11390`, provides an exhaustive critique of the pros and cons of this proposal. We remark that the work to be carried out under the intent of this proposal will undoubtedly provide invaluable insight, but several limitations there are circumvented here. Here we summarize the key differences between the CAMT proposal and this one.

- *Movement.* The CAMT proposal (Proposal II) studies movement at a very fine spatio-temporal scale through the use of particle tracking models. This approach will likely provide invaluable insight into the mechanistic underpinnings of movement, but a potential difficulty is scaling up the results of such simulation studies to obtain spatial distributions across the delta smelt range. Further, while it is proposed to use existing trawl data to calibrate the particle tracking models, there is some conern about the utility of trawl data to be informative to this scale of a process because of "false" zeroes and coarse spatiotemporal resolution. In contrast, movement here is proposed to be measured empirically through collection of new data and modeled in a regression style framework. The intention of the new monitoring is to obtain density descriptions at fine enough spatial and temporal resolution to measure population level location shifts in the overall habitat range.

- *Survival.* How entrainment affects the delta smelt population is proposed by the CAMT to be measured in the same way as Kimmerer [20], with improvements to the parameters and volume expansions used to convert spatially resolved densities to spatially resolved abundances. As discussed above, we believe a competing risks formulation that attempts to separate natural from entrainment related mortality is more appropriate. We acknowledge that if natural mortality is too variable in space and time, and if the Entrainment Zone is very dynamic in space and time with respect to its boundaries, then it will be difficult to completely separate out the entrainment related mortality.

- *Data.* The CAMT proposal relies on salvage data to obtain estimates of proportional entrainment and aggregated trawl catch data at seasonal scales (Proposals I, III, and IV). We attempt to side-step the difficulties in using salvage data given its uncertain relationship with entrainment by framing the analysis in such a way that these data are not required. However, we will evaluate its utility using information-theoretic and model diagnostic techniques. Data aggregation has limited utility for serving as a real time, predictive tool for measuring the relationship between environmental covariates, spatio-temporal population dynamics of delta smelt, and water management operations.

- *Synthesis.* How the CAMT proposal quantifies population level effects of entrainment (Proposal IV) will be accomplised by updating the life-cycle model of Maunder and Deriso [23] to include new covariates, more data, and revised assumptions about survival. The proposal is currently unspecific as to how entrainment related covariates will be specifically included so it is difficult to know at this time what the exact procedure will be. Our proposal attempts to measure the impacts of entrainment through calculations and comparison of population growth rates in the presence and absence of entrainment. *A shortcoming in our proposal for estimating population level effects of water exports is the absence of measurement and analysis of entrainment on pre-adult life stages, i.e. entrainment of the larvae and juvenile life-stages.*

C Details of the DSEM and DSEE Introduced in Section 7

C.1 Details of the DSEM

Section 7.2 summarized the proposed monitoring procedure as a temporally repeated stratified two stage sample, and presented a simulation-based analysis of sample size effects on the precision of entrainment related estimates. In this section we focus on two issues, the sensitivity of the sample size results to input values and more realistic assessments using spatially patterned densities and spatial sampling procedures. We start by giving a brief description of the initial density calculations used in the simulation.

The Bay Delta was divided into 29 subregions, as described in the DSLCM [8]. A ratio of means density estimate was calculated for each subregion by dividing the mean smelt catch by the mean sample volume. Because not all 29 subregions were sampled by the SKT survey in February 2015, density estimates from neighboring subregions were used to impute missing densities (see Table C.5). Subregion densities were then multiplied by estimates of the corresponding subregion water volumes (down to 4 meters), and by a factor of 2/3, to yield subregion abundance estimates. The 2/3 factor comes from assuming that the density of smelt in the water column decreases linearly from the surface to 4 meters, below which it is 0. This is in contrast to the assumption that the density is uniform across the first 4 meters of the water.

Finally, the subregions were stratified according to areas of high and low smelt density within the LZ and HZ. The density in each stratum was estimated as the ratio of the mean subregion abundance and the mean subergion volume (as calculated over the subregions within the stratum).

Table C.5: Subregions indicated on the left were not sampled during the February 2015 SKT survey. The catch density from the corresponding subregion on the right was used as a substitution for the missing density.

Unsampled Subregion	Substitute Subregion
East San Pablo Bay	Carquinez Strait
Upper Napa River	Lower Napa River
Sacramento River Ship Channel	Cache Slough and Liberty Island
Franks Tract	Holland Cut
Middle River	Mildred Island
Upper San Joaquin River	San Joaquin River near Stockton
Victoria Canal	Old River
Grant Line Canal and Old River	San Joaquin River near Stockton
Rock Slough and Discovery Bay	Holland Cut

Sensitivity of sample size determinations. The simulation-based results are particularly sensitive to the entrainment related mortality in the Entrainment Zone and to the initial density inputs. Keeping the same initial densities used in Section 7.2, the effects of decreasing the entrainment related mortality from 0.5 to 0.1 (i.e. $\exp(-E)$=0.9) can be seen in Tables C.6 and C.7 and Figure C.5. The percentage of times that negative estimates of entrainment occurred has quadrupled for some combinations of m and q, compared to the situation where entrainment related mortality was 50%.

Table C.6: Percentage of times $d_{t,\mathrm{En}}$ was negative.

Locations per Stratum	Tows per Location: **2**	**4**	**6**	**8**
2	43.5%	41.2%	40.1%	40.1%
4	41.8%	40.5%	38.7%	36.9%
6	41.3%	37.4%	34.5%	33.5%

Table C.7: Mean CV for proportional entrainment, $\tilde{n}_{t_0}$, when entrainment related mortality is 0.1 (in contrast to Table 2).

Locations per Stratum	Tows per Location: **2**	**4**	**6**	**8**
2	768.8%	504.6%	431.5%	412.4%
4	591.7%	432.2%	361.0%	296.9%
6	466.3%	309.5%	265.7%	245.9%

The fact that delta smelt are now a relatively rare species, with oftentimes sparse densities, has a considerable effect on the precision of estimates. If the initial densities were two orders of magnitude larger, the percentages of times where entrainment estimates are negative declines considerablyc as do the CVs for $d_{t,\mathrm{En}}$ (compare Tables C.8 and C.9 to Tables C.6 and C.7).

Table C.8: Percentage of times $d_{t,\mathrm{En}}$ was negative. Results are based on entrainment related mortality of 10%.

Locations per Stratum	Tows per Location: **2**	**4**	**6**	**8**
2	10.6%	1.6%	3.9%	0.8%
4	4.2%	0.1%	0.7%	0.0%
6	1.7%	0.2%	0.2%	0.0%

Table C.9: Mean CV for proportional entrainment, $\tilde{n}_{t_0}$, when initial densities are increased 100-fold. Results are based on entrainment related mortality of 10%.

Locations per Stratum	Tows per Location: **2**	**4**	**6**	**8**
2	79.8%	57.7%	46.8%	41.4%
4	57.0%	40.5%	33.7%	28.8%
6	46.9%	33.1%	27.2%	23.4%

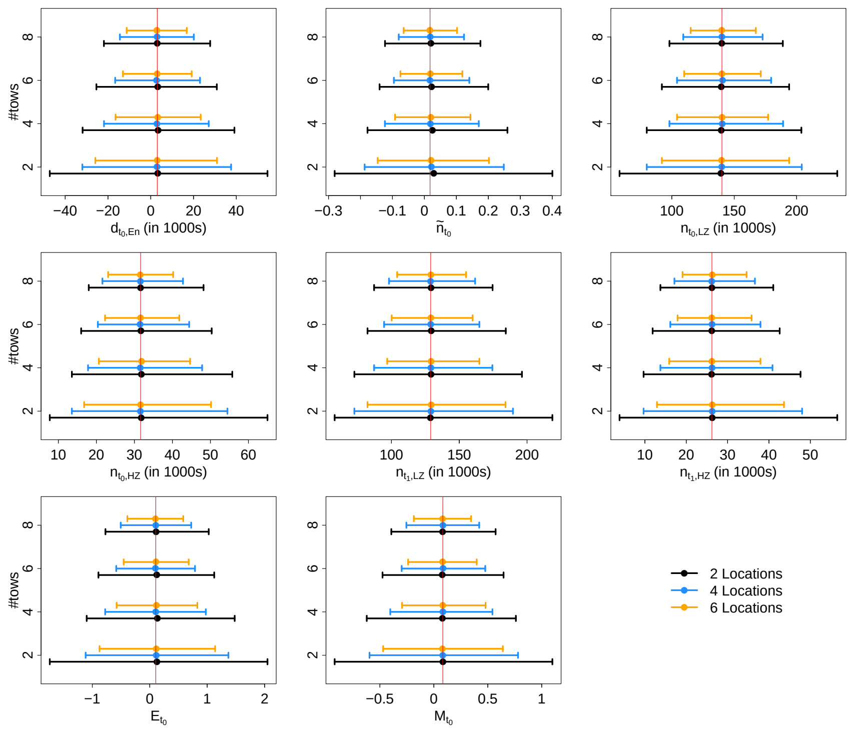

Figure C.5: Empirical means and 95% confidence intervals for eight parameters (defined below) based on simulations from a two-stage sampling design with varying numbers of sampling locations per stratum and tows per location. In contrast to Figure 4, the entrainment mortality rate has changed from 0.5 to 0.1. Each mean and corresponding confidence interval is based on 5000 simulations. Vertical red lines indicate "true" values used to generate the data. Parameters shown are: $d_{t_0,E}$ (number entrained between t_0 and t_1), $\tilde{n}_{t_0}$ (proportional entrainment between t_0 and t_1), $n_{t_0,LZ}$ (LZ abundance at t_0), $n_{t_0,HZ}$ (HZ abundance at t_0), $n_{t_1,LZ}$ (LZ abundance at t_1), $n_{t_1,HZ}$ (HZ abundance at t_1), E_{t_0} (entrainment related mortality between t_0 and t_1), and M_{t_0} (natural mortality between t_0 and t_1).

Spatial density processes and spatial sampling. Spatially independent simulation of densities (at the primary sampling unit level) as was done using the Poisson distribution does not yield realistic results based on spatial patterns in delta smelt density seen in the Spring Kodiak Trawl survey. Figure C.6 shows GAM-smoothed predictions of delta smelt densities for February 2008 SKT survey data.

The GAM results are based on fitting the SKT data collected from 2002-2014 to the following semi-parametric model. Let t denote the Julian Day (JD) a sample was collected where JD is relative to 1 January of the year of the sample, m_t the month in which t belongs, and y the year of the survey. The catch on day t of year y at sampling location station stn was modeled as

$$catch_{t,y,stn} \sim \text{NegBin}\left(\mu_{t,y,stn}, \theta\right)$$

with overdispersion parameter θ and mean $\mu_{t,y,s}$ modeled as

$$\begin{aligned} \ln(\mu_{t,y,s}) = \ln(Vol_{t,y,stn}) + \beta_0 + \beta_1 Secchi_{t,y,stn} + \beta_2 Conductivity_{t,y,stn} + \\ \sum_{i=3}^{5} I_i \beta_i TideStage_{t,y,stn} + \beta_6 t + \sum_{i=7}^{18} I_i \beta_i c + \sum_{i=19}^{30} I_i \beta_i t * c + s_{m_t,c}(Long_s, Lat_s) \end{aligned} \tag{11}$$

where the βs are the coefficients to be estimated, β_0 is the effect of the factor covariates at reference levels $TideStage = Ebb$ and year $c = 2002$, I_i are indicator variables taking the value one corresponding to whether the factor variables of cohort and tide are associated with the observation, $*$ denotes an interaction, and m_t is the month containing t. The water quality covariates $Secchi$, $Conductivity$, and $TideStage$ are values measured by the SKT survey at the station at the time of sampling, with the first three covariates being continuous valued and the last covariate tacking categorical values of "Ebb", "High Slack", "Low Slack", and "Flood". This model has fixed coefficients across time for the environmental covariates, different "intercept" and JD 'demographic decline" coefficients for each year, and a different nonparametric spatial smooth for each month-year. Continuous water quality predictor variables were standardized prior to fitting, and the model was fit using the `gam` function from the `mgcv` package [24] in R v3.1.0 [25].

GAM based predictions of catch y_i were made over a set of locations throughout the region separated by 9m in each direction. Spatially smoothed covariate values were used for input values at each grid location. Given a design matrix $\mathbf{X}_i$ containing a set of fixed covariate values at a location i in the collection of locations, the parameter vector $\hat{\boldsymbol{\beta}} = \left[\hat{\beta}_0, \ldots, \hat{\beta}_n\right]^\top$ of coefficients from the fitted model, and a prediction volume $Volume_p$, a prediction of catch $Y_i = \log_e(y_i)$ on the linear scale is given by $Y_i = \mathbf{X}_i \hat{\boldsymbol{\beta}} + \log_e(Volume_p)$. The predicted density at location i on the response scale is

$$\delta_i = y_i / Volume_p = \exp\left(Y_i\right) / Volume_p$$

Figure C.6 shows a result of these predicted densities for a particular month and year: higher densities in the more northern portions of the Bay Delta (e.g. Suisun Marsh and Cache Slough) are evident in contrast to considerably lower densities in the more westerly regions (e.g. eastern San Pablo Bay).

Rather than simple random samples being used to select the Primary Sampling Units (stage one sampling), spatial sampling designs, such as regular grids or generalized random-tesselation stratified (GRTS) design [13] could be applied to the GAM results. One version of regular grid sampling is to randomly superimpose an oversized grid of evenly spaced points on a map of the area and points which lie in the area become the sample locations. The GRTS design is considerably more sophisticated. It begins with “a function that maps two-dimensional space into one-dimensional space, thereby defining an ordered spatial address”, the addresses are randomly ordered, and then another transformation is applied to yield a linear structure. Systematic sampling of this linear structure yields “a spatially well-balanced random sample”. Stevens and Olsen 2004 [13] also discuss the use within GRTS of variable probability sampling (VPS; [26]), where sample locations are selected with probability based on relevant covariates. One of these two approaches, a regular grid or GRTS, are recommended for selecting the PSUs in practice.

Presumably, given a spatial pattern to delta smelt densities and an appropriate spatial sample design, the sample sizes to achieve a specified level of precision, e.g. confidence interval widths for $d_{t,\mathrm{En}}$, will be smaller than those predicted based on a spatially heterogeneous density field and simple random sampling.

Finally, we note that spatio-temporal process models [27] could be used as an alternative to the spatially smoothed GAMs for simulating the density field. Such models can provide parametric explanations of the spatial (and temporal) relationships as opposed to the nonparametric smooths used in the GAMs. Such models could potentially be used as part of the entrainment estimation process (DSEE, see the next section).

Future research will be focused on methods for more realistic spatial modeling of the density and spatial sampling procedures.

C.2 Details of the DSEE

C.2.1 Estimating Abundance from the DSEM Data

Given a region r (either the LZ or the HZ), assume there are H_r strata within it; figure 2 illustrates the case where $r = 2$ and $H_r = 2$ for each r. For notational simplicity, consider a single moment in time t (corresponding to a time interval), a single strata $h \in H_r$ with m total sampling locations, where q_i tows at each location i, $i = 1 \ldots m$ are made. Then the strata level abundance is given by

$$\hat{n}_h \quad = \quad V_h \frac{1}{m} \sum_{i=1}^{m} \overline{\delta}_i = V_h \frac{1}{m} \sum_{i=1}^{m} \left[\frac{\sum_{j=1}^{q_i} y_{i,j}}{\alpha p_g \sum_{j=1}^{q_i} v_{i,j}} \right], \tag{12}$$

where V_h is the volume of water in strata h that is considered delta smelt habitat, $\overline{\delta}_i$ is the estimated density at sampling location i, $y_{i,j}$ and $v_{i,j}$ are the number of delta smelt caught, and volume of water sampled, on tow j at location i, respectively, and p_g is an estimate of gear efficiency (perhaps date specific but will be assumed to be 1 initially). The parameter α adjusts the estimate to account for possible inhomogeneity in the vertical distribution of fish. For example, assume the density decreases linearly from the surface to a maximum depth of 4m. Because the Kodiak Trawl samples only the top 2m of water, estimated abundances using water volume expansions to 4m depth would be biased upwards. Setting $\alpha = 1.5$ corrects this bias (assuming a linear decrease in density to 0 at 4m depth). The total estimated abundance

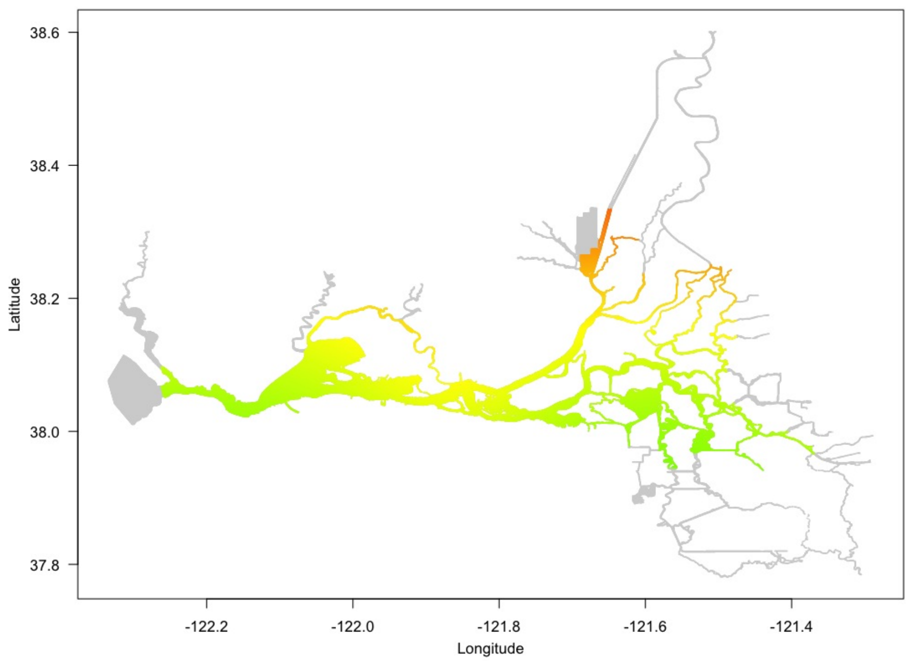

Figure C.6: Delta smelt density (fish/10,000m^3) predictions in space for the month of February 2008 based on a spatio-temporal GAM model fit to SKT survey data. Cool values denote low densities, warm values denote higher densities, grey values are potential smelt habitat where predictions are not made due to being too far outside the spatial range of survey stations.

in region r is then

$$\hat{n}_r = \sum_{h=1}^{H} \hat{n}_h. \tag{13}$$

Remarks

- Eq.'n 12 will be modified if variable probability sampling within strata is employed. See [26].
- Standard errors of the estimates of abundance can also be calculated.

C.2.2 Model Fitting

Given a collection of bivariate abundance estimates $\hat{\mathbf{n}}_t = (\hat{n}_{t,\text{LZ}}, \hat{n}_{t,\text{HZ}})^\mathsf{T}$ for $t = 1, \ldots, T$, and a population dynamics model such as given by eq'ns 1-10 in Section 6, the model can be fit using conditional (nonlinear) least squares [28]. The vector of parameters to be estimated is $\theta = (\alpha_0, \alpha_1, \gamma_0, \beta_0, \beta_1)$. For simplicity cohort specific notation is suppressed. Given estimates of abundance and a parameter vector θ_{est}, the predicted abundances from eq'ns 3 and 4 are

$$n_{t+1,\text{LZ}} = \exp(-M_t)\rho_t \hat{n}_{t,\text{LZ}} \tag{14}$$

and

$$n_{t+1,\text{HZ}} = \exp(-(M_t + E_t))\left((1-\rho_t)\hat{n}_{t,\text{LZ}} + \hat{n}_{t,\text{HZ}}\right) \tag{15}$$

and the conditional sum of squares is

$$S_c(\theta_{\text{est}}) = \sum_{t=2}^{T}\left[(\hat{n}_{t,\text{LZ}} - n_{t,\text{LZ}})^2 + (\hat{n}_{t,\text{HZ}} - n_{t,\text{HZ}})^2\right]. \tag{16}$$

The parameter vector $\hat{\theta}$ that minimizes $S_c(\theta_{\text{est}})$ over θ_{est} are the conditional least squares paremeter estimates used for making inference.

Remarks

- The use of normally distributed observation error is not strictly required. Alternative formulations may involve rounding abundance estimates to the nearest integer and using a negative binomial probability distribution, NB $(\mu_{t,r}, k_{t,r})$ to describe observations, where the $\mu_{t,r}$ are given by the deterministic predictions of eq'ns 3 and 4 and the dispersion parameters $k_{t,r}$ are estimated.
- If substantial movement from the LZ to the HZ is thought to occur in only one time interval t', then it may be more pragmatic to fix ρ_t at zero for $t \neq t'$.
- The conditional least squares approach for model fitting and parameter estimation outlined above in eq'ns 14-16 is just one of several ways to fit and conduct statistical inference with time series models. For completeness we remark on a few others that could be used. (1) A process noise only model fit by maximum likelihood [29], which requires an assumption about an error distribution for the observations and maximizing the resulting likelihood function. When the process noise is assumed to be normally distributed, the conditional least squares estimates and the maximum likelihood estimates of θ are the same. (2) An observation error only model fit by maximum likelihood or least squares (see e.g. [29] or [30]). (3) A state-space model that includes both process noise and observation error fit by numerical integration or in a Bayesian framework using stochastic sampling techniques (see e.g. [30] and [31]; also see [32] for combining Bayesian and frequentist strategies for model fitting and inference). (4) A number of approaches (response surface methodology, feedforward neural networks, and thin-plate splines) as described in [33] and [34] are a potential option.
- In addition to the relatively data intensive fitting procedures listed above, method of moments (MoM) can be used to estimate survival and entrainment. MoM, although needing relatively little data and thus potentially useful for "back of the envelope" calculations of survival and entrainment (but not simultaneously movement) at the beginning of each field season. For example, assuming no movement $n_{t+1,\text{LZ}}/n_{t\text{LZ}} = \exp(-M)$ and $n_{t+1,\text{HZ}}/n_{t,\text{HZ}} = \exp(-(M + E_t))$. Thus the ratio of the survival $S_{t,\text{HZ}}$ in the HZ to the survival $S_{t,\text{LZ}}$ in the LZ is calculated as

$$\frac{S_{t,\text{HZ}}}{S_{t,\text{LZ}}} = \frac{\exp(-(M+E_t))}{\exp(-M)} = \frac{n_{t+1,\text{HZ}}/n_{t,\text{HZ}}}{n_{t+1,\text{LZ}}/n_{t,\text{LZ}}}, \tag{17}$$

the entrainment related mortality term is estimated by

$$E_t = -\ln\left[\frac{n_{t+1,\mathrm{HZ}}/n_{t,\mathrm{HZ}}}{n_{t+1,\mathrm{LZ}}/n_{t,\mathrm{LZ}}}\right] \tag{18}$$

and the total number entrained is estimated by

$$d_{t,\mathrm{En}} = \frac{E_t}{M+E_t}\left(1-\exp(-(M+E_t))\right) n_{t,\mathrm{HZ}}. \tag{19}$$

However, such approaches can yield implausible (e.g. negative estimates of entrainment) results when estimates of total abundances in the LZ and HZ are not very precise and/or substantial movement has occured between time t and $t+1$.

- Simultaneous estimation of movement and survival subprocesses using just LZ and HZ abundance estimates alone cannot be done without making further assumptions. Making assumptions about relationships between the movement probabilities and measurable environmental covariates such as proposed in eq'ns 9 and 10 allows estimation of movement and survival subprocesses by constraining the number of parameters in the model.

D A Simulation Model to Assess Estimability of Declines in Survival Due to Direct and Indirect Sources of Entrainment

Overview

Simulation studies were conducted to assess the estimability of a model describing smelt density fluctuations in time and space as a function of two sub-processes, movement and survival, where survival is further decomposed into two sources of mortality, natural and entrainment related. The model is fit using up to three data types: absolute abundances in two spatial fregions, and total salvage counts from the CVP and SWP pumping stations. While abundance data in each spatial region is required, salvage data is not necessarily needed to estimate the sub-processes of interest, so we study model estimation with and without salvage data. Overall, parameter estimates, although sometimes correlated with each other, generally had low bias. Using salvage data helped improve (reduce bias and variance) estimates of the different sources of mortality but not movement parameters. Estimating initial abundances, rather than assuming them known, only trivially reduced accuracy of most parameter estimates, with the exception of the natural survival parameter, whose mean and variance increased substantially. In general, even when observated data (alternatively density estimation accuracy) was simulated with a coefficient of variation as high as approximately 0.4, parameter estimation was feasible and qualitative identification of relationships was correct. We discuss possible model shortcomings.

D.1 Model

D.1.1 Spatial and Temporal Framework

The model assumes two spatial regions, a low risk zone (LZ) within which only natural mortality affects survival, and a high risk zone (HZ), within which survival is simultaneously affected by both natural mortality and an additional entrainment related source of mortality. The spatial regions are geographically static (i.e. they are constant in time and space), and movement is unidirectional from the LZ to the HZ with the proportion of the LZ population moving to the HZ based on a dynamic hydrological covariate. The LZ was defined by the Far West (excluding the Mid San Pablo Bay subregion), West, and North regions as defined in the DSLCM [8] with the exception of the Lower San Joaquin subregion, which was assigned to the HZ region along with the DSLCM defined South region. The temporal resolution of the model was weekly. For model fitting purposes, all covariates were standardized, i.e. covariate x is transformed to x^* where $x^* = (x - \overline{x})/\sigma_x$.

D.1.2 Process Models

The two sub-processes considered in this simulation study are movement and survival. As noted in Section 6 of the main text, cohorts are not linked through time via a birth sub-process, so we suppress cohort specific notation for clarity. The sequence of subprocesses was first movement and then survival; i.e. $\mathbf{n}_{t+1} = \mathbf{S}_t\mathbf{M}_t\mathbf{n}_t$, where $\mathbf{n}_t$ is a 2×1 matrix denoting the abundance of cohort c during week t in the LZ and HZ, and $\mathbf{M}_t$ and $\mathbf{S}_t$ are 2×2 matrices described next.

Movement model- As noted above, movement is assumed to be unidirectional from the LZ to the HZ. The movement matrix $\mathbf{M}_t$ for cohort c during week t is given by

$$\mathbf{M}_t = \begin{bmatrix} 1-\rho & 0 \\ \rho & 1 \end{bmatrix} \tag{20}$$

with ρ depending on an environmental covariate. The probability of movement from the LZ to the HZ during week t of cohort c was modeled as

$$\rho_t = \text{expit}(\beta_0 + \beta_1 SJRFlow_t)$$

where $SJRFlow_t$ is the standardized weekly mean San Joaquin River outflow.

Survival model- Mortality rates due to to natural and entrainment related causes are denoted by M and E_t, respectively. The survival matrix $\mathcal{S}_t$ is given by

$$\mathbf{S}_t = \begin{bmatrix} \exp(-M) & 0 \\ 0 & \exp(-(M+E_t)) \end{bmatrix} \tag{21}$$

Natural mortality M was assumed to be constant through time (and across cohorts) and was parameterized as

$$M = \exp(\gamma_0).$$

Entrainment related mortality E_t, the additional mortality incurred in the HZ, was assumed to depend on Clifton Court Forebay mean weekly turbidity, denoted by $CCFB_t$, mean weekly OMR, denoted by OMR_t, and (possibly) their interaction. Entrainment mortality was modeled as

$$E_t = \exp(\alpha_0 + \alpha_1 OMR_t + \alpha_2 CCFB_t + \alpha_3 CCFB_t * OMR_t).$$

D.1.3 Data Models

Possible sources of data in week t of cohort c are estimated abundances in the LZ and HZ regions, $\hat{n}_{t,LZ}$ and $\hat{n}_{t,HZ}$ respectively, and salvage data $\hat{n}_{t,s}$. These were each modeled as independent and identically distributed random variables with negative binomial distribution NB(μ_i, θ_i) parameterized with expectation μ_i and variance $\mu_i + \mu_i^2/\theta_i$, for $i \in 1, 2, 3$, where $\mu_1 = n_{t,\text{LZ}}$, $\mu_2 = n_{t,\text{HZ}}$, and $\mu_3 = n_{t,s}$. For data generation, the θ_i's must be a priori chosen along with the sub-process model parameters, while in model fitting they are estimated. Although $n_{t,LZ}$ and $n_{t,HZ}$ are specified from the sub-process models, it remains to specify $n_{s,t}$, the number in salvage. The number salvaged is some fraction Ψ_t of the number entrained $d_{t,\text{En}}$, where $d_{t,\text{En}}$ is given by eq'n 7

in Section 6 of the main text. The fraction Ψ_t was modeled as a function of export volume, with the motivation being (see [22]) that higher exports should result in decreased residency time of delta smelt in regions of high predator density (e.g. Clifton Court Forebay) which decreases the predation rate and hence increases salvage. Φ_t was modeled as

$$\Psi_t = \psi_0 + \psi_1 exports_t$$

where $exports_t$ is the standardized daily mean total export volume in week t.

D.1.4 Data Generation

Data generation consisted of the following steps:

1. *Set initial abundances and distribution*- We used SKT and covariate data from the 2001-2002 through 2009-2010 cohorts to tie the range of abundances in the simulation model to empirical data. The time indexing associates week 1 (December 1 through December 7) with $t = 1$, and the value $\mathbf{n}_t$ corresponds to the abundance at the beginning of each week, prior to movement and survival for that week. The initial abundances $\mathbf{n}_1$ were obtained by taking the mean total abundance based on volumetrically scaling SKT estimates of density for each cohort (i.e. average density in cohort c across surveys from January through May) and multiplying by 1.1. As the 2002-2003 cohort has no January 2003 SKT, and January abundance is often the greatest, we multiplied the 2002-2003 mean cohort abundance by 1.2. Yearly means were used rather than only including January (or February) abundances because in some years total adult estimates using a naive volumetric scaling approach result in substantially higher total adult smelt abundances in February compared with January, which is not likely, and resulted in initial abundances that were unrealistically small (see Table D.1 for initial abundances used).

2. *Compute sub-process values*- The parameter values shown in Table D.2 and covariate data were used to calculate $\mathbf{M}$ and $\mathbf{S}$ matrices. Figure D.1 shows the probabilities of movement, survival, and proportion of entrainment in salvage for the parameter values in Table D.2 and the empirically recorded covariate data. For the chosen $\gamma_0 = -5$, the constant natural (weekly) survival is $\exp(-M) = \exp(-\exp(\gamma_0)) = \exp(-\exp(-5))$ which is approximately 99%.

3. *Generate "true" abundances*- Generate J time series of true abundances. For a given cohort, stochastic true abundances at time step t in time series j were generated as follows, where $rB(n, p)$ denotes a random number drawn from a binomial distribution with size n and probability p, and the subscript j is dropped for clarity:

   (a) The proportion staying in the LZ prior to survival is $n^*_{t,LZ} = rB(n_{t,LZ}, 1 - \rho_t)$.

(b) The number surviving in the LZ is $n_{t+1,LZ} = rB(n^*_{t,LZ}, \exp(-M))$.

(c) The number in the HZ after movement by individuals from the LZ is $n^*_{t,HZ} = n_{t,HZ} + n_{t,LZ} - n^*_{t,LZ}$.

(d) The number surviving in the HZ is $n_{t+1,HZ} = rB(n^*_{t,LZ}, \exp(-(M + E_t)))$

(e) The number entrained during week t is $\tilde{n}_{t,E} = E_t/(M + E_t)(n^*_{t,HZ} - n_{t,HZ})$

(f) The number salvaged during week t is $n_{s,t} = rB(\tilde{n}_{t,E}, \Psi_t)$

4. *Generate estimated abundances*- For each set of true abundances $j \in J$, generate K replicate observations for $k = 1, ..., K$ by selecting a number from the following distributions:

$$n_{t,LZ,obs_{j,k}} \sim \text{NB}(n_{t,LZ,true_j}, \theta_1)$$
$$n_{t,HZ,obs_{j,k}} \sim \text{NB}(n_{t,HZ,true_j}, \theta_2)$$
$$n_{s,t,obs_{j,k}} \sim \text{NB}(n_{s,t,true_j}, \theta_3)$$

To explore how observation variability influenced estimability, the θ parameters were chosen from the set $\{5, 10, 15, 20, 40, 60, 80, 100\}$; see figure D.2 and footnote 0 for discussion of size parameter settings. In each study $\theta_1 = \theta_2 = \theta_3$, and for each change in the θ's a new set of (stochastic) true observations were generated.

Table D.1: Initial abundances by cohort to initiate simulations.

Cohort	2001-2002	2002-2003	2003-2004	2004-2005	2005-2006
LZ	1,502,063	1,451,464	1,163,315	799,606	322,526
HZ	388,291	124,667	352,838	35,019	16,826

Cohort	2006-2007	2007-2008	2008-2009	2009-2010
LZ	637,661	567,342	1,363,309	536,054
HZ	40,020	2,693	3,633	0

Table D.2: Values used to define sub-processees.

	Movement		Survival					Salvage	
Parameter	β_0	β_1	γ_0	α_0	α_1	α_2	α_3	ψ_0	ψ_1
True value	-3	0.1	-5	-2	-0.1	0.1	0	-2	0.1

D.1.5 Model Fitting

A collection of $K = 300$ simulated datasets of estimated abundances per a single set of simulated abundances j, $j = 1, \ldots, J$ were used to evaluate parameter estimability and correlation assuming 6 different models, summarized in Table D.3. In this simulation study $J = 1$ so only replicates across a single true time series were considered. In general, the models varied in the data they used, either using both abundance and salvage estimates or only abundance estimates,

[0]For a random variable X that is NB distributed with mean μ and size parameter θ, the variability is $\mu + \mu^2/\theta$. For total abundance values in the range of those used to initiate the simulations (see Table D.1), the variance of a NB distribution can be quite large. For example, if there are one million fish, $\mu = 1e6$, and assuming $\theta = 1$, then the variability is on the order of 1e12. To constrain this variability we chose θ parameters so that observations would be within approximately 20% of the mean approximately 90% of the time. This was done as follows. For $\mu = 1e6$, $P[X \leq 0.8m] = 0.05$ when $\theta \approx 61.57$, and $P[X > 1.2m] = 0.05$ when $\theta \approx 72.99$.

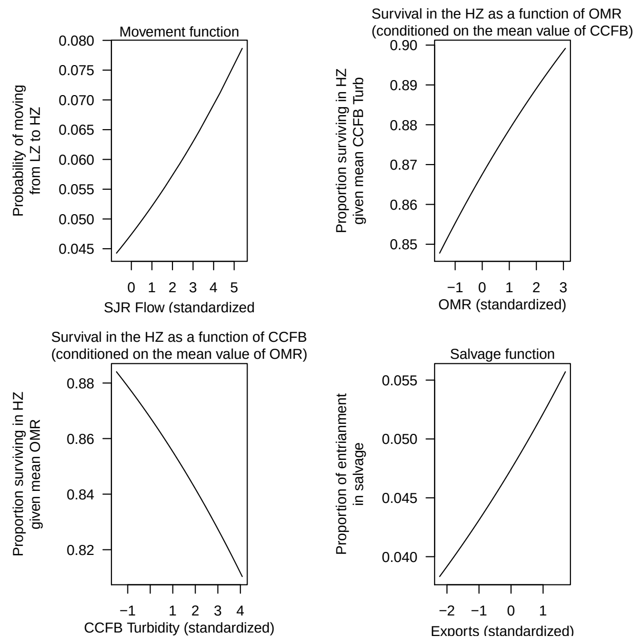

Figure D.1: Sub-process values for the parameters chosen in Table D.2.

and the number of sub-processes assumed to be known exactly. Models were fit to the simulated datasets by maximum likelihood using the `optim` function in R v3.1.0 [25].

Table D.3: Summary of estimated models.

Model	Data used	Description
1	Catch data only	Everything known but γ_0 and α_0
2	Catch data only	Known initial abundances and movement.
3	Catch data only	Known initial abundances.
4	Catch data only	Nothing known.
5	Catch and salvage data	Known initial abundances, movement, and salvage parameters.
6	Catch and salvage data	Known initial abundances and movement parameters.
7	Catch and salvage data	Known initial abundances.
8	Catch and salvage data	Nothing known.

D.2 Results

D.2.1 Results Across Models when Observation Noise Parameterθ was set to 60.

This results subsection explores in some detail parameter estimation issues when $\theta = 60$ across the suite of models shown in Table D.3. Tables D.4, D.5,D.6, and D.7 show the bias, variance, MSE, and CV of the parameter estimates for the different models considered. Figures D.3 and D.4 show example scatterplots of pairs of estimated parameters (other model and θ combinations show similar correlations).

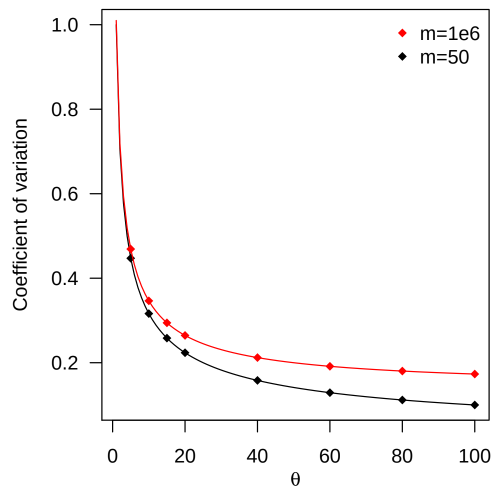

Figure D.2: The relationship between the coefficient of variation (CV) and the size parameter θ of the negative binomial distribution for which $CV = \sqrt{\mu + \mu^2/\theta}/\mu$, with results for two values of μ shown. Filled diamonds are drawn at the locations of the θ parameters used in the simulation study.

D.2.2 Varying Observation Noise Parameter θ

This subsection focuses on parameter estimates for Model 3, perhaps the most likely model to be used in practice, across different levels of observation noise. Parameter estimate bias does not appear to change, while variance decreases, with increasing θ. Figure D.4 shows that correlation between estimates of key parameter parameter pairs (movement and natural survival, movement and entrainment related survival, and natural and entrainment survival) is not removed with better estimates of the true abundance. However, estimates of the sub-processes was generally accurate even with large observation noise, with Figure D.5 showing an an example of the estimated relationship between survival and CCFB turbidity. Figure D.6 show how the different models in Table D.3 perform as measured by their ability to estimate total and proportional entrainment, respectively.

D.3 Discussion

Given the correct model specification (i.e., the right set of covariates are used in the appropriate sub-process models which are in turn correctly described), parameter estimation accuracy was qualitatively accurate the vast majority of the simulations (generally $> 90\%$ for each scenario). Although there is correlation between the movement, natural survival, entrainment related survival, and salvage intercept parameters, generally the parameters were accurately estimated. Notably, changing the observation noise (estimation accuracy) did not remove parameter correlation. This is perhaps because in each simulation the underlying true process contains sub-processes acting in a multiplicative (sequential) way. Yet even when abundance estimates were very noisy, the sub-processes were mostly estimated qualitatively accurately and had low bias, variance, MSE, and CV.

This simulation study described movement and survival as functions of environmental covariates, and critically there were always smelt to "respond" to the environmental covariates. In reality, it is feasible that local environmental conditions would exist that would provide favoriable habitat for delta smelt, or otherwise influence delta smelt movement and survival, yet there would no impact on the delta smelt abundance and distribution because of absence of individuals in the local area.

Three types of process misspecification warrant discussion. A first type of model misspecification concerns movement. Movement was modeled (and estimated) as a function of an approximately smoothly changing, single environmental covariate. A more accurate model may be one in which the environmental covariate is not smoothly changing, but rather changes abruptly to "trigger" movement such as a storm event which abruptly increases flow and turbidity, sometimes called a "first flush" [35]. Further, what determines movement into the HZ may not be best captured by a single environmental covariate such as turbidity or outflow in the lower San Joaquin River, but rather may be a combination of spatially disparate factors such as flow and turbidity in the Sacramento River relative to flow and turbidity in the San Joaquin River, or the source of turbidity in relation to the tidal stage [36]. Lastly, at some point in time upstream spawning migration will not occur even if a clear environmental signal is present that normally would trigger movement because smelt have ceased spawning. Lastly, each of these complexities can presumably interact to necessitate a very complex movement model.

A second type of model process misspecification concerns survival. Here we assumed a spatially and temporally constant natural survival rate. Accomodating at least cohort specific changes in natural survival could be relatively easily explored, while estimating spatial changes in natural survival would be more difficult. In the HZ, distinguishing between spatially and temporally varying natural survival and entrainment would likely not be possible, but this might only be a problem of semantics.

The third type of model process misspecification possibility concerns salvage, a fraction of direct entrainment. Here, including salvage data, although strictly not necessary, helped inform parameter estimation by reducing bias and variance. However, this assumed a correct match between both the covariate used to model salvage and the structural form of the entrainment salvage relationship. Whether the benefits of including salvage data if the model was incorrect remains to be studied. More broadly, distinguishing between direct (mortality because of reaching inhospitable habitat of pumps and canals) and indirect (e.g. elevated predation rates related to entrainment or inability to spawn in a preferred habitat type) sources of entrainment related mortality would not be possible with only the catch and salvage data discussed here, but these processes underpin mechansitic explanations of changing survival rates. Little is known about the probability of direct entrainment as a function of space, time, and environmental covariates at spatiotemporal resolutions finer than seasonal scales and no space. Grimaldo et al. (2009) [7] showed a relationship between OMR and salvage data at a seasonal scale, while Castillo et al. [22] found a complex relationship between the number of marked fish recorded in salvage with where and when they were released and what exports were.

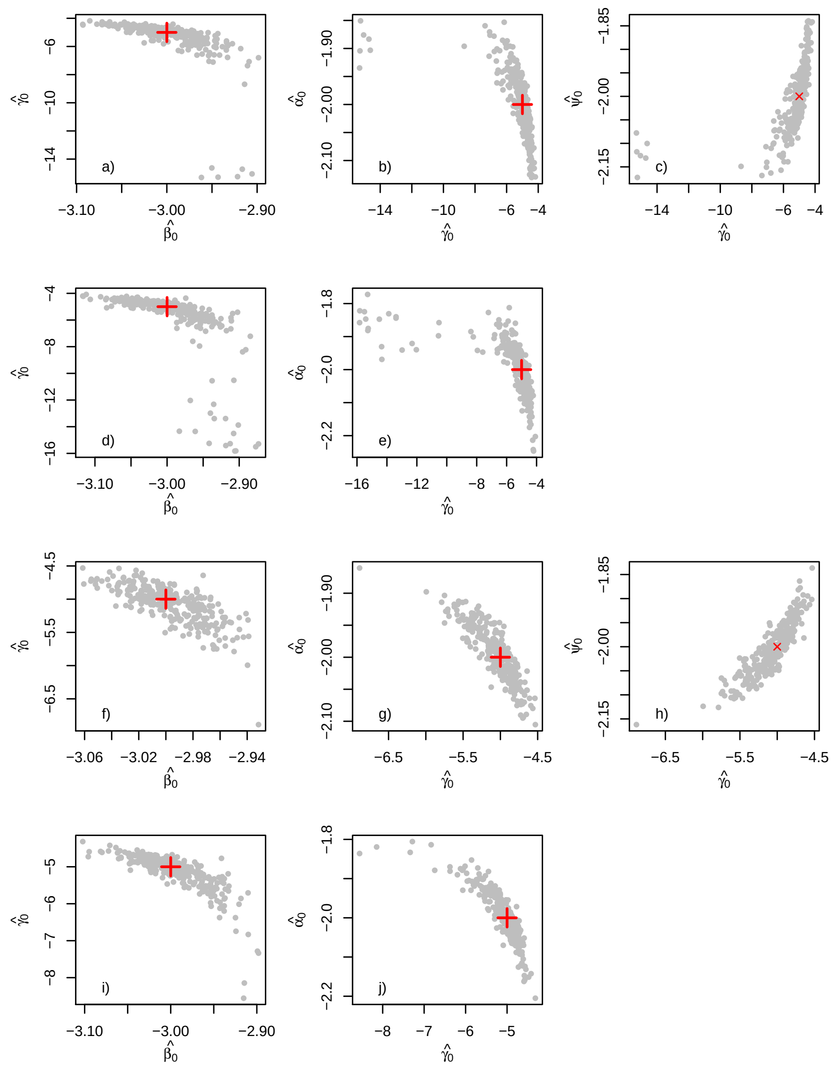

Figure D.3: Parameter correlation between selected parameter pairs of parameter estimates (grey dots), with the true parameter pair located at the red x, from model M8 (panels a-c), model M4 (panels d-e), model M7 (panels f-h), and model M3 (panels i-j).

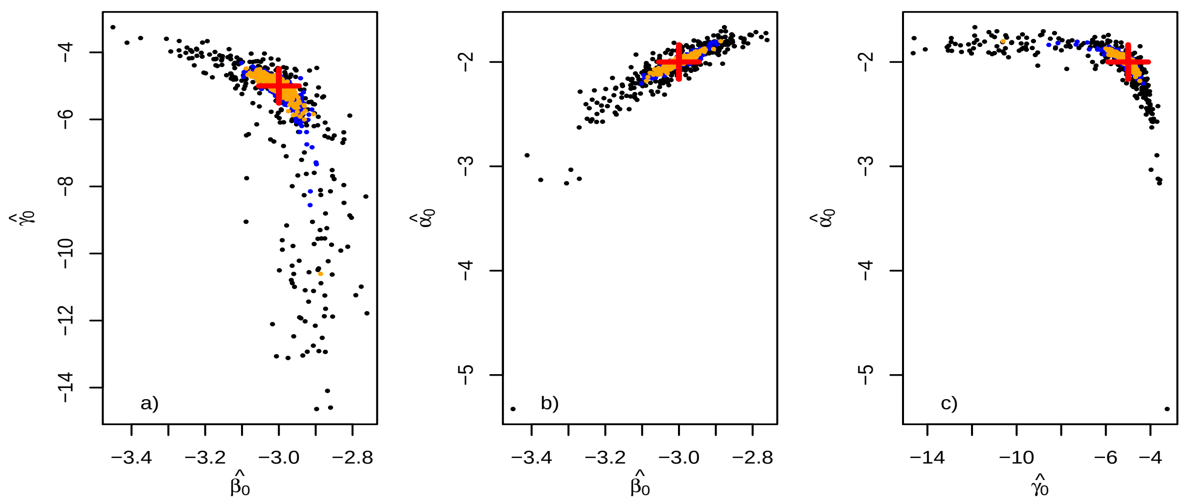

Figure D.4: Scatterplots of selected pairs of parameter estimates of model M3 when $\theta = 5$ (black dots), $\theta = 60$ (blue dots), and $\theta = 100$ (orange dots). Red crosses denote the true parameter values. As θ gets larger the variation of the estimates around the true values decreases. Alternatively, larger observation noise (estimation uncertainty) weakens the correlation, although it is still present (especially in the middle panel).

Table D.4: Bias of the parameter estimates when abundance and salvage estimates are generated with $\theta = 60$. True values of the parameters are shown in parentheses at the top of each column.

	Observation Noise			Movement		Survival					Salvage	
Model	θ_1 (60)	θ_2 (60)	θ_3 (60)	β_0 (−3)	β_1 (.1)	γ_0 (−5)	α_0 (−2)	α_1 (−0.1)	α_2 (0.1)	α_3 (0)	ψ_0 (−2)	ψ_1 (0.1)
1						-0.0234	0.0009					
2	0.0119	0.0251				-0.0264	0.0014	0.0017	-0.0008	-0.0000		
3	0.0155	0.0341		0.0041	-0.0017	-0.1368	0.0068	0.0021	-0.0018	-0.0011		
4	0.0580	0.1108		0.0043	-0.0016	-0.6645	0.0048	0.0012	-0.0015	0.0008		
5	0.0080	0.0088	0.0035			-0.0235	0.0030	0.0022	-0.0005	0.0015		
6	0.0118	0.0106	0.0118			-0.0226	0.0017	0.0019	-0.0004	0.0016	0.0017	-0.0004
7	0.0134	0.0162	0.0179	0.0036	-0.0003	-0.0752	0.0066	0.0026	-0.0006	0.0015	-0.0047	0.0006
8	0.0476	0.0744	0.0458	0.0021	-0.0011	-0.3195	0.0023	0.0019	-0.0005	0.0020	0.0009	-0.0002

Table D.5: Variance of the parameter estimates when abundance and salvage estimates are generated with $\theta = 60$. True values of the parameters are shown in parentheses at the top of each column.

	Observation Noise			Movement		Survival					Salvage	
Model	θ_1 (60)	θ_2 (60)	θ_3 (60)	β_0 (−3)	β_1 (.1)	γ_0 (−5)	α_0 (−2)	α_1 (−0.1)	α_2 (0.1)	α_3 (0)	ψ_0 (−2)	ψ_1 (0.1)
1						0.0271	0.0004					
2	0.0130	0.0122				0.0281	0.0005	0.0005	0.0004	0.0008		
3	0.0132	0.0121		0.0014	0.0003	0.2500	0.0042	0.0007	0.0005	0.0009		
4	0.0141	0.0134		0.0021	0.0004	4.9516	0.0062	0.0010	0.0008	0.0014		
5	0.0130	0.0121	0.0140			0.0103	0.0002	0.0002	0.0001	0.0001		
6	0.0130	0.0121	0.0144			0.0255	0.0005	0.0002	0.0001	0.0001	0.0005	0.0003
7	0.0132	0.0123	0.0147	0.0007	0.0002	0.0794	0.0018	0.0003	0.0001	0.0001	0.0028	0.0004
8	0.0140	0.0139	0.0161	0.0013	0.0002	2.2929	0.0033	0.0004	0.0001	0.0001	0.0048	0.0005

Table D.6: Mean squared error of the parameter estimates when abundance and salvage estimates are generated with $\theta = 60$. True values of the parameters are shown in parentheses at the top of each column.

	Observation Noise			Movement		Survival					Salvage	
Model	θ_1 (60)	θ_2 (60)	θ_3 (60)	β_0 (−3)	β_1 (.1)	γ_0 (−5)	α_0 (−2)	α_1 (−0.1)	α_2 (0.1)	α_3 (0)	ψ_0 (−2)	ψ_1 (0.1)
1						0.0277	0.0004					
2	0.0131	0.0128				0.0288	0.0005	0.0006	0.0004	0.0008		
3	0.0134	0.0133		0.0014	0.0003	0.2687	0.0042	0.0007	0.0005	0.0009		
4	0.0175	0.0257		0.0021	0.0004	5.3932	0.0062	0.0010	0.0008	0.0014		
5	0.0130	0.0122	0.0140			0.0108	0.0002	0.0002	0.0001	0.0001		
6	0.0131	0.0122	0.0145			0.0260	0.0005	0.0003	0.0001	0.0001	0.0005	0.0003
7	0.0134	0.0125	0.0150	0.0007	0.0002	0.0850	0.0019	0.0003	0.0001	0.0001	0.0029	0.0004
8	0.0163	0.0194	0.0182	0.0013	0.0002	2.3950	0.0033	0.0004	0.0001	0.0002	0.0048	0.0005

Table D.7: Coefficient of variation of parameter estimates when simulated observations are generated with $\theta = 60$. True values of the parameters are shown in parentheses at the top of each column.

	Observation Noise			Movement		Survival					Salvage	
Model	θ_1 (60)	θ_2 (60)	θ_3 (60)	β_0 (−3)	β_1 (.1)	γ_0 (−5)	α_0 (−2)	α_1 (−0.1)	α_2 (0.1)	α_3 (0)	ψ_0 (−2)	ψ_1 (0.1)
1						-0.0328	-0.0106					
2	0.0277	0.0268				-0.0334	-0.0116	-0.2379	0.2043	-2608.1629		
3	0.0280	0.0267		-0.0125	0.1842	-0.0973	-0.0324	-0.2703	0.2232	-26.4803		
4	0.0286	0.0275		-0.0154	0.1903	-0.3928	-0.0394	-0.3200	0.2782	44.1467		
5	0.0277	0.0268	0.0289			-0.0202	-0.0063	-0.1284	0.1086	7.4466		
6	0.0277	0.0268	0.0292			-0.0318	-0.0109	-0.1608	0.1110	7.3827	-0.0117	0.1697
7	0.0280	0.0269	0.0294	-0.0085	0.1352	-0.0555	-0.0216	-0.1772	0.1114	7.7373	-0.0266	0.1871
8	0.0286	0.0283	0.0306	-0.0121	0.1417	-0.2847	-0.0289	-0.1958	0.1141	5.9480	-0.0346	0.2199

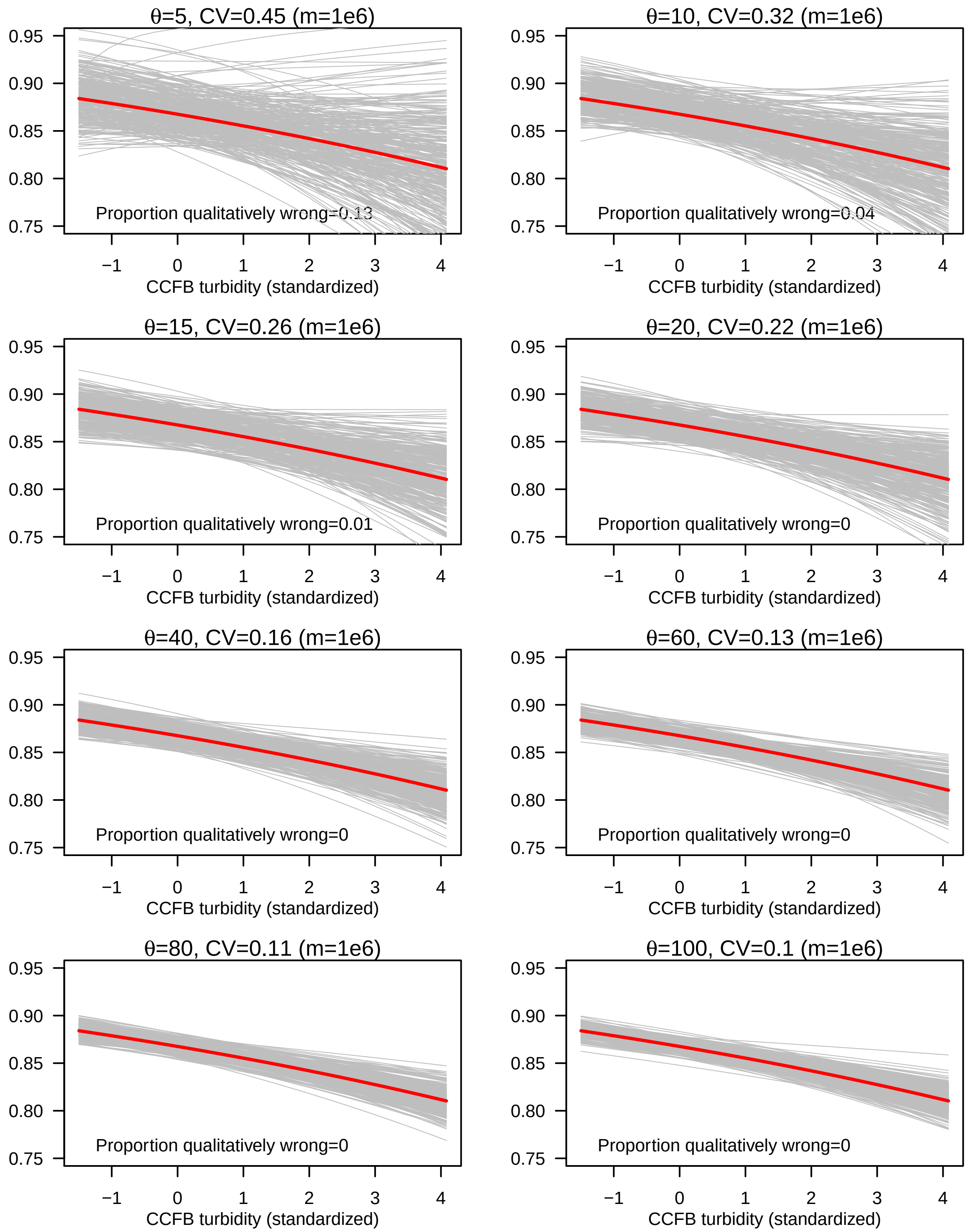

Figure D.5: Entrainment related survival sub-process estimates of model 3 of Table D.3 across different values of observation noise θ. Each panel shows estimates of the survival sub-process at the mean value of OMR across the 100 simulations and across the different values of CCFB, in grey, for different values of θ. The true curve to be estimated is shown in red. The proportion qualitatively wrong numbers show rounded percentages of the number simulations that estimated the slope of the sub-process relationship with respect to its covariate incorrectly.

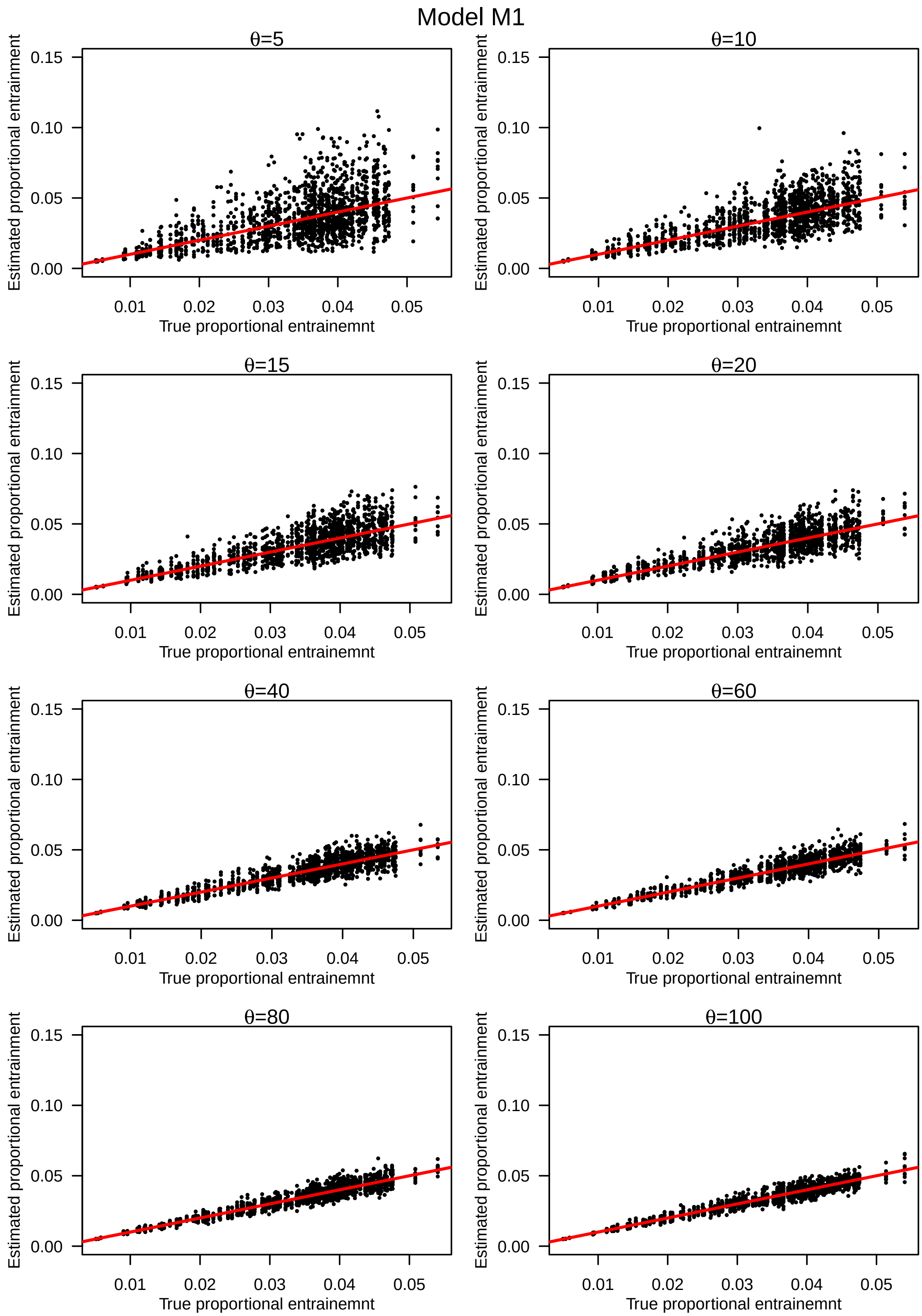

Figure D.6: Estimated vs. true proportional entrainment for model M3 and different observation noise values of θ. Estimated vs. true proportional entrainment from other fitted models show simlar qualitative patterns. The red line is the 45° line.

E A Sketch of Within-Year Management to Achieve Specific Population Recovery Level

Overview

One approach to management of delta smelt is (a) to set goals for recovery such as a particular increase in population abundances by a specific date, and (b) to achieve these goals via informed management actions, which are modified and updated as new information becomes available. Here we outline how a recovery strategy can be quantified in terms of a target annual growth rate when the goal is a specified change in the population size $\Lambda_{g,T}$ over a specified time period T into the future (e.g. $\Lambda_{g,T} = 1.10$, a 10% increase in the population over $T = 10$ years). By analyzing how the adjusted annual growth rate target changes given an observed set of growth rates $\{\lambda_{t,obs}, t = 1, ..., T' < T\}$, we show that overcoming early cumulative deficits requires greater adjustments in the target growth rate than if early cumulative growth rates were such that the population was larger than the target goal. We provide a model and analysis framework to predict what growth rates will be needed to achieve future population abundance goals given knowledge about current and past abundances.

E.1 Target, and Adjusted Target, Annual Growth Rates

Suppose that given an abundance n_0 at some reference time $t = 0$, management specifies a goal of achieving a specific abundance by year T, n_T. Thus the total growth rate, relative to n_0, is $\Lambda_{g,T} = n_T/n_0$; equivalently, $n_T = \Lambda_{g,T} n_0$. The abundance n_T can be written as the product of n_0 and yearly growth rates, i.e. $n_T = \lambda_1\lambda_2 \cdots \lambda_T n_0 = n_0 \prod_{i=1}^{T} \lambda_i$, which has the geometric mean growth rate of $\bar{\lambda}_{g,T} = \left(\prod_{i=1}^{T} \lambda_i\right)^{1/T}$. Given the abundance goal n_T, the geometric mean equals the Tth root of $\Lambda_{g,T}$, $\bar{\lambda}_{g,T} = (\Lambda_{g,T})^{1/T}$, which we label the *target annual growth rate*.

As time progresses, up to time $T' < T$, a series of realized (observed) growth rates results. These growth rates certainly do not equal the target annual growth rate, i.e., either $\prod_{t=1}^{T'} \lambda_{t,obs} < \bar{\lambda}_{g,T}^{T'}$ or $\prod_{t=1}^{T'} \lambda_{t,obs} > \bar{\lambda}_{g,T}^{T'}$. Conditional on the realized growth rates, one can define an *adjusted target growth rate* as

$$\bar{\lambda}_{g,T-T'} = \left[\frac{\Lambda_{g,T}}{\prod_{t=1}^{T'} \lambda_{t,obs}}\right]^{1/(T-T')} \tag{22}$$

If the adjusted target growth rate was to be maintained for the remaining $T - T'$ years, then the overall desired total growth rate $\Lambda_{g,T}$ would be achieved.

Figure E.1 shows an example of how $\bar{\lambda}_{g,T-T'}$ in eq'n 22 changes as a function of $\prod_{t=1}^{T'} \lambda_{t,obs}$ for different values of T' given a specified $\Lambda_{g,T}$ and T. Categorizing progress toward the goal n_T simplistically, locations toward the left end of the x-axis are "bad", i.e., progress has been slow, and locations toward the right end are "good", i.e., progress has been rapid. If we write $c = \prod_{t=1}^{T'} \lambda_{t,obs}$ and express eq'n 22 as an explicit function of c,

$$\bar{\lambda}_{g,T-T'}(c) = \left[\frac{\Lambda_{g,T}}{c}\right]^{1/(T-T')}$$

then it is easy to see that $\bar{\lambda}_{g,T-T'}(c)$ is a declining function with positive curvature (Fig. E.1). Thus, for a given value of c, the change to $c+\Delta c$ results in a smaller change in $\bar{\lambda}_{g,T-T'}$ than for the change $c-\Delta c$.

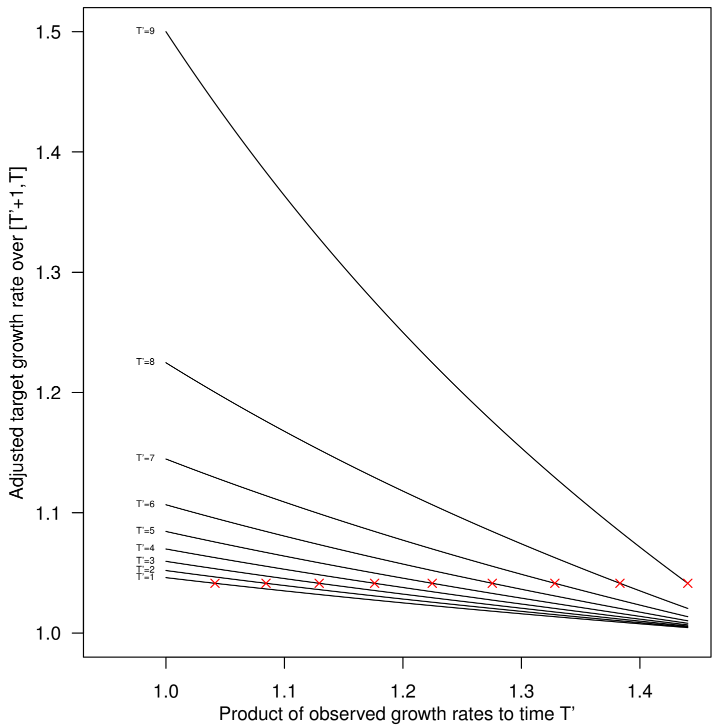

Figure E.1: Example of adjusted target growth rates vs. the product of observed growth rates; see eq'n 22. In this example $\Lambda_{g,T} = 1.5$, $T = 10$, and hence $\bar{\lambda}_{g,T} = (1.5)^{1/10} \approx 1.04$. Each line gives the relationship for a specified value of T', indicated to the left of the corresponding curve. The pairs $\left(\left(\bar{\lambda}_{g,T}\right)^{T'}, \bar{\lambda}_{g,T}\right)$ for $T' = 1, ..., 9$ are shown as red crosses. The lines intersect these red crosses when the adjusted target value is equal to the target value $\bar{\lambda}_{g,T}$.

E.2 Managing Winter Survival Towards Achieving Target Growth Rates

Management actions are typically targeted at specific life stages and in particular spatially defined regions. To incorporate a notion of annual growth rate goals into life-stage and region specific management actions, a spatially resolved population dynamics model is required (see Section E.2.1) and then investigation of exact way in which management acts on survival must be modeled (see Section E.2.2)

E.2.1 A Spatio-Temporal Model to Describe Within Cohort Population Dynamics

Assume we have a spatial partition of the habitat that divides it into r distinct regions (e.g. into an area with potential entrainment related mortality and an area where only natural mortality occurs), with region specific fecundity, survival, and movement processes. Then decomposing the population dynamics into A sequential time periods within a cohort, the population can be described by

$$n_{t+1} = \left(\prod_{a=1}^{A} \mathbf{M}_{a,t+1} \mathbf{S}_{a,t+1} \right) \mathbf{B}_{t+1} n_t \tag{23}$$

where $\mathbf{B}$, $\mathbf{S}$, and $\mathbf{M}$, are $r \times r$ matrices representing births, survival, and movement, respectively, in each region and time period.[5]

E.2.2 Managing Winter Movement and Survival to Achieve a Target Growth Rate

For delta smelt, one way in which the population is managed is through minimizing entrainment related losses of pre-spawning adults during the winter months of approximately December-March. This suggests that we can set $A = 2$ in eq'n 23 to represent two time periods, one before these management actions occur, and one during which these management actions occur. By letting $n_t^* = \mathbf{M}_{1,t+1}\mathbf{S}_{1,t+1}\mathbf{B}_{t+1}n_t$, then $n_{t+1} = \mathbf{M}_{2,t+1}\mathbf{S}_{2,t+1}n_t^*$. This indicates that given knowledge of n_t and n_t^*, achieving a target population abundance n_{t+1} will depend on how feasible adjustment of the values in $\mathbf{S}_{2,t+1}$ and $\mathbf{M}_{2,t+1}$ are relative to the goal.

For simplicity, assume that entrainment is only possible in a region of habitat that does not change (labeled region 2), so that there are a total of two regions. Denote the fraction surviving in region 1 by $\exp(-M_{t+1})$ and the fraction surviving in region 2 by $\exp(-(M_{t+1} + E_{t+1}))$, reflecting natural mortality M_{t+1} and an additional entrainment related mortality E_{t+1}. Then the survival matrix during period $a = 2$ is given by

$$\mathbf{S}_{2,t+1} = \begin{bmatrix} e^{(-M_{t+1})} & 0 \\ 0 & e^{(-(M_{t+1}+E_{t+1}))} \end{bmatrix} \tag{24}$$

Denote the proportion of the population in region r moving out of region r by ρ_r. Then the movement matrix is given by

$$\mathbf{M}_{2,t+1} = \begin{bmatrix} 1-\rho_1 & \rho_2 \\ \rho_1 & 1-\rho_2 \end{bmatrix} \tag{25}$$

Assume

$$\begin{aligned} M_{t+1} &= f_1(\text{environmental conditions over time period 2}) \\ E_{t+1} &= f_2(\text{environmental conditions and water operations over time period 2}) \\ \rho_{1,t+1} &= f_3(\text{environmental conditions and water operations over time period 2}) \\ \rho_{2,t+1} &= f_4(\text{environmental conditions and water operations over time period 2}) \end{aligned}$$

and that we have functional forms and parameter values for the functions $f_i, i \in \{1, 2, 3, 4\}$. Then we can use eq'ns 23-25 to predict what annual growth rate will be achieved under different hypothesized future environmental conditions and water operations given n_t and n_t^*.

[5] The sub-processes of survival and movement during any particular time period a_i in eq'n 23 can further refined temporally with little additional modifications. For example, the end result of movement $\mathbf{M}_{a,t+1}$ during time period a can be written as the product of a series of movement matrices operating over finer time scales $\{a_{i,1}, a_{i,2}, ..., a_{i,n}\}$ where $a_i = \cup\{a_{i,1}, a_{i,2}, ..., a_{i,n}\}$, so that $\mathbf{M}_{a,t+1} = \prod_{j=1}^{n} \mathbf{M}_{a_{i,j},t+1}$. Such a decomposition would facilitate analysis of management impacts over finer time scale horizons, such as done during weekly or bi-weekly water operations and in relation to first flush storm events.

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